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Buyer Commitment in Bilateral Bargaining: The Case of Online Japanese C2C Market

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Abstract

This paper studies bargaining when buyers can continue searching for alternative sellers while negotiating, which limits their commitment to complete a transaction. Using transaction level data from a Japanese online marketplace, I document frequent post-agreement nonpurchase and show that buyers who explicitly pledge immediate payment are more likely to have their offers accepted, renege less often, and complete transactions faster. I develop and estimate a dynamic bargaining model with buyer search and limited commitment. Counterfactuals that restrict search during bargaining show that increased buyer commitment can reduce total welfare. Sellers especially those with higher valuations benefit from the elimination of delays and walkaways and respond by raising list prices. This reduces buyer welfare by lowering the option value of search and increasing expected list prices. Platform revenue also declines because buyer behavior shifts away from counteroffers and negotiated prices fall.

Keywords: Bargaining, Search, Platform Design

JEL Codes: C61, D12, D83, L86, D47

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1 Introduction

Negotiation between a buyer and a seller often takes place alongside buyer search. In housing markets, buyers typically negotiate with a seller while simultaneously continuing to visit and make offers on alternative properties. Similarly, in car purchases, buyers may solicit and compare quotes from multiple dealers before committing to a transaction. In online marketplaces, where price negotiation has become increasingly common, buyers can both haggle with a given seller and continue searching for alternative listings offering better terms. Despite the prevalence of such environments, existing empirical studies of bargaining typically analyze each bargaining interaction in isolation. As a result, we lack systematic evidence on how the availability of search during negotiation shapes bargaining outcomes in real-world settings.

Search availability during bargaining can undermine buyer commitment. Depending on the bargaining protocol, a buyer may walk away during negotiations or even renege after reaching an agreement if a better outside option becomes available. This has emerged as a practical concern on several online marketplaces, including eBay, Etsy, Facebook Marketplace, and Mercari. For example, sellers on eBay have long reported frustration with buyers who fail to complete purchases after their counteroffers are accepted, resulting in delayed or unpaid transactions. In response, eBay introduced an immediate payment feature that automatically charges the buyer upon offer acceptance (EcommerceBytes (2021)). Despite the use of such commitment enhancing policies, their welfare implications for buyers, sellers, and platforms remain poorly understood. Understanding these implications requires analyzing not only how individual bargaining outcomes change but also how platform-wide equilibrium objects, such as the distribution of listing prices, respond.

This paper builds and estimates a structural model of bargaining with search and quantifies the welfare impact of requiring buyer commitment. In the model, a searching buyer randomly matches with a seller and enters a price negotiation. A key feature is that the buyer may not be committed to suspending further search during bargaining, which can generate delay and even reneging after an agreement is reached. The model predicts endogenous sorting into commitment status, with high valuation buyers choosing to be committed not to search during bargaining and sellers optimally accepting lower offers only from committed buyers.

I use detailed offer level data from the Japanese online marketplace Mercari. I exploit a unique feature of the data that records all textual communication exchanged during price negotiations. Using this information, I find evidence of endogenous sorting into commitment status, reflected in some buyers explicitly pledging immediate payment. These buyers complete transactions with substantially shorter delays and are significantly less likely to renege than buyers who do not make such pledges. Consistent with the model's predictions, sellers are also more willing to accept lower counteroffers from buyers who signal commitment.

I then take the model to the data, focusing on used 128 GB iPhone 7 listings. I provide constructive identification arguments for the key model primitives, including buyer and seller valuations, buyer and seller arrival rates, and the buyer search cost. These identification results exploit the optimality of counteroffers under complete information bargaining together with observed buyer choice probabilities across sellers. At the benchmark value, the estimated flow search cost is 1,478 yen per day, which corresponds to about 10.2% of the median buyer valuation.

In my counterfactual, I simulate the introduction of a buyer commitment policy by making search during bargaining prohibitively costly. The results show that a full commitment policy reduces overall welfare by 20.2 yen per listing and platform revenue by 22.7 yen per listing. Sellers benefit on average, with gains increasing in seller valuation, because the elimination of search induced delays that were concentrated among high valuation sellers raises continuation values and lowers the opportunity cost of raising list prices and being declined. Buyers face higher expected list prices ex-ante and lose the option value of searching during bargaining, which reduces buyer welfare across the distribution, with larger losses for higher valuation buyers who were more likely to purchase at list prices in the baseline. The platform loses because buyer behavior shifts away from counteroffers toward outright declines and because accepted counteroffer prices fall, and these losses outweigh the gains from eliminating walkaways and from higher list prices.

2 Literature

This paper contributes to three strands of the literature. The first is the empirical analysis of bargaining. Recent work in this area makes use of the availability of detailed offer level data, particularly from online marketplaces such as eBay. These data allow researchers to study bargaining behavior at a fine level of detail, including comparisons of theoretical models (Backus, Blake, Larsen, et al. (2020)), measurement of inefficiencies and bargaining breakdowns (Larsen (2021); Freyberger and Larsen (2025)), the role of verbal communication (Backus, Blake, Pettus, et al. (2020)), fairness considerations (Keniston et al. (2021)), and the effects of timing and delay in negotiation (Fong and Waisman (2025)). While most existing studies analyze bargaining interactions in isolation, this paper adopts a structural approach that embeds bargaining within a competitive market environment and explicitly models inter-bargaining dynamics. This perspective highlights the importance of equilibrium effects for interpreting observed offers and bargaining outcomes.[1]

Secondly, this paper contributes to the empirical literature on platform design. Existing studies examine a wide range of design features, including search algorithms (Fradkin (2017); Dinerstein et al. (2018)), pricing mechanisms (Einav et al. (2018)), reputation systems (Resnick et al. (2006); Nosko and Tadelis (2015)), and the role of user profiles (Edelman et al. (2017)). In contrast, empirical work on the design of bargaining protocols remains limited. One notable exception is Zhang et al. (2021), who studies bargaining features on the Chinese platform Taobao and simulates the effects of a platform wide ban on price negotiations. However, due to the absence of detailed offer level data, the bargaining component of their structural model is necessarily reduced form, which limits its ability to evaluate changes in the bargaining protocol beyond an outright ban. This paper instead focuses on a more practically prevalent design issue, namely unpaid items arising from bargaining interactions, and uses a structural approach to evaluate the consequences of alternative bargaining rules for buyers, sellers, and platform revenue.

Lastly, this paper contributes to the literature examining the interaction between search

[1] Methodologically, this paper is related to empirical work that studies dynamic strategic interaction on online marketplaces, including Adachi (2016), Hendricks and Sorensen (2018), Backus and Lewis (2025), and Bodoh-Creed et al. (2021).

and bargaining. Much of the existing work is theoretical. For example, Chikte and Deshmukh (1987) study a model without recall, implying that past offers cannot be revisited and bargaining delays do not arise, while Lee (1994) and Chatterjee and Lee (1998) allow for recallable offers and show that buyer search can generate delays. Empirically, Allen et al. (2019) study a negotiated price market in which consumers can search for competing offers, modeling multilateral bargaining as an auction conditional on search to quantify welfare losses from search frictions and price discrimination. Barkley et al. (2025) study the residential housing market as a search environment with both auctions and price negotiations under two sided incomplete information, modeling negotiation through a direct mechanism design approach. In contrast, my work abstracts from multilateral bargaining and two sided incomplete information but explicitly models the bargaining protocol itself, allowing counterfactual analysis of practically relevant platform rules governing commitment, delay, and enforcement.

3 Institution

Mercari, Japan's largest online C2C marketplace for second hand products, facilitates over 100 million transactions annually. The platform enables users to buy and sell a wide range of products, from handicrafts to automobiles. A seller creates a listing that includes photos, a description, and a chosen list price. Buyers may immediately purchase the product at the listed price on a first come first served basis, or attempt to negotiate a price reduction. During my sample period from 2020 to 2021, negotiation was not a formal platform feature but instead took place publicly in the comment section of each listing. Figure 1 presents an illustrative listing page, and Table 1 provides a stylized example of a comment based negotiation. When a seller and buyer agree on a price reduction in the comments, the seller updates the listing price accordingly. The buyer may then purchase the item at the revised price, but no mechanism binds the buyer to complete the transaction. If another buyer arrives, that buyer can purchase the item at the updated price, provided the seller does not revert the price after nonpurchase by the original buyer. Similar to eBay, post agreement buyer reneging is a widespread issue on Mercari (All About (2023)).

Figure 1: Annotated listing interface with English labels.

Note: This figure shows an example listing page in the Mercari iPad application. The image is provided by Mercari and does not correspond to any particular listing. A small on screen indication of price negotiation appears below the image on the right. During my sample period from 2020 to 2021, negotiation was not a formal platform feature and occurred through the public comment section, although comment based negotiation remained possible even after formalization.

Table 1: Illustrative negotiation via the public comment section (stylized example)

Timestamp	User	Comment
2020 Nov 17 10:12	Buyer A	Hello. I am considering purchasing. If the device is unlocked and there is no SIM restriction, would you be willing to sell it for 12,000 yen?
2020 Nov 17 10:18	Seller	Thank you for your message. Yes, I can accept 12,000 yen. The device is unlocked and has no SIM restriction.
2020 Nov 17 10:25	Buyer A	Thank you.
2020 Nov 17 10:31	Seller	I have updated the listed price to 12,000 yen.

Notes: This table is a stylized illustration of a typical negotiation in a public comment section. It does not relate to any particular listing.

4 Model

4.1 Setup

Time is continuous. Sellers and buyers have valuations for a homogeneous good distributed according to F_S and F_B, respectively, both absolutely continuous with respect to Lebesgue measure. Buyers incur a common search cost c per day, and all agents share a common continuous discount rate r. Each agent's valuation, the search cost, and the discount rate are common knowledge. There are N_S sellers and N_B buyers in the market, and the platform collects a fraction $t = 0.10$ of each realized sale. The sequence of events and payoffs is depicted in Figure 2. Consider a seller with valuation s, who first chooses a list price p^0. Buyers arrive to this seller according to a Poisson process with rate λ_S, and each arriving buyer's valuation is drawn from F_B. From the buyer's perspective, sellers arrive according to a Poisson process with rate λ_B. Upon matching with seller s, a buyer with valuation b chooses one of three actions: purchase at the list price (A), make a counteroffer p^1 (C), or decline (D). If the buyer chooses A, trade occurs immediately at price p^0 between buyer b and seller s. When a trade occurs at price p between buyer b and seller s, the buyer receives payoff $b - p$ and the seller receives payoff $(1 - t)p - s$, and both agents exit the market. If the buyer chooses D, the match dissolves. The seller receives continuation value $U_S(s)$. The buyer resumes search after an exogenously given delay governed by a Poisson process with rate λ_R and then obtains continuation value $U_B(b)$. I refer to λ_R as the *response rate* and assume $\lambda_R > \lambda_B$.

If the buyer chooses C, the seller response, either to accept the offer p^1 (A) or to decline it (D), arrives at the response rate λ_R. If the seller chooses D, the match is dissolved, with the seller receiving $U_S(s)$ and the buyer instantly resuming search and receiving $U_B(b)$. If the seller chooses A, the buyer's opportunity to complete the purchase arrives at the response rate λ_R. At the time of choosing action C, the buyer also decides whether to continue searching for another seller (S) or not (N). If she chooses S, she continues to search and faces the arrival of a new seller with valuation $s' \sim F_S$ at Poisson rate λ_B, incurring the search cost c per unit of time until arrival. In this case, if the original seller chooses A, the buyer retains the option to purchase from the original seller at price p^1 until the arrival of the new seller.[2]

[2]For simplicity, I assume that the arrival of the new seller always occurs after the arrivals of the original

Upon the arrival of the new seller, the buyer either chooses to purchase from the original seller (P), in which case trade occurs at price p^1 between buyer b and seller s, or to walk away to the new seller (W). When the buyer chooses W, her match partner becomes the new seller s'. Even in this case, with exogenously given probability κ, the seller trades at price p^1 with a buyer whose behavior is outside the model. Otherwise, the seller becomes unmatched and receives continuation value $U_S(s)$.

From a match between a seller s and a buyer b, the seller receives a continuation value $V_S(s,b)$ and the buyer receives $V_B(s,b)$. The continuation value of an unmatched seller with valuation s is given by

$$U_S(s) = \frac{\lambda_S}{\lambda_S + r} \int V_S(s,b)\, dF_B(b),$$

while the continuation value of an unmatched buyer with valuation b is

$$U_B(b) = \frac{\lambda_B}{\lambda_B + r} \int V_B(s,b)\, dF_S(s) - \frac{c}{\lambda_B + r}.$$

4.2 Equilibrium

I restrict attention to a subgame-perfect Nash equilibrium that is both stationary and in steady state. Stationarity refers to the strategy profile: a player's equilibrium action depends only on its own valuation and, if matched, on the valuation of the currently matched counterpart. Steady state refers to the market environment: the valuation distributions F_S and F_B, as well as the measure of active sellers and buyers N_S and N_B, remain constant over time. In steady state, market entry exactly offsets exit. Whenever a seller exits the market upon a completed trade, a new seller with the same valuation enters the market, and analogously for buyers. Under the Poisson meeting process, this implies a flow-balance condition equating total meeting rates on the two sides of the market:

$$\lambda_B N_B = \lambda_S N_S \tag{1}$$

seller response and the buyer purchase opportunity.

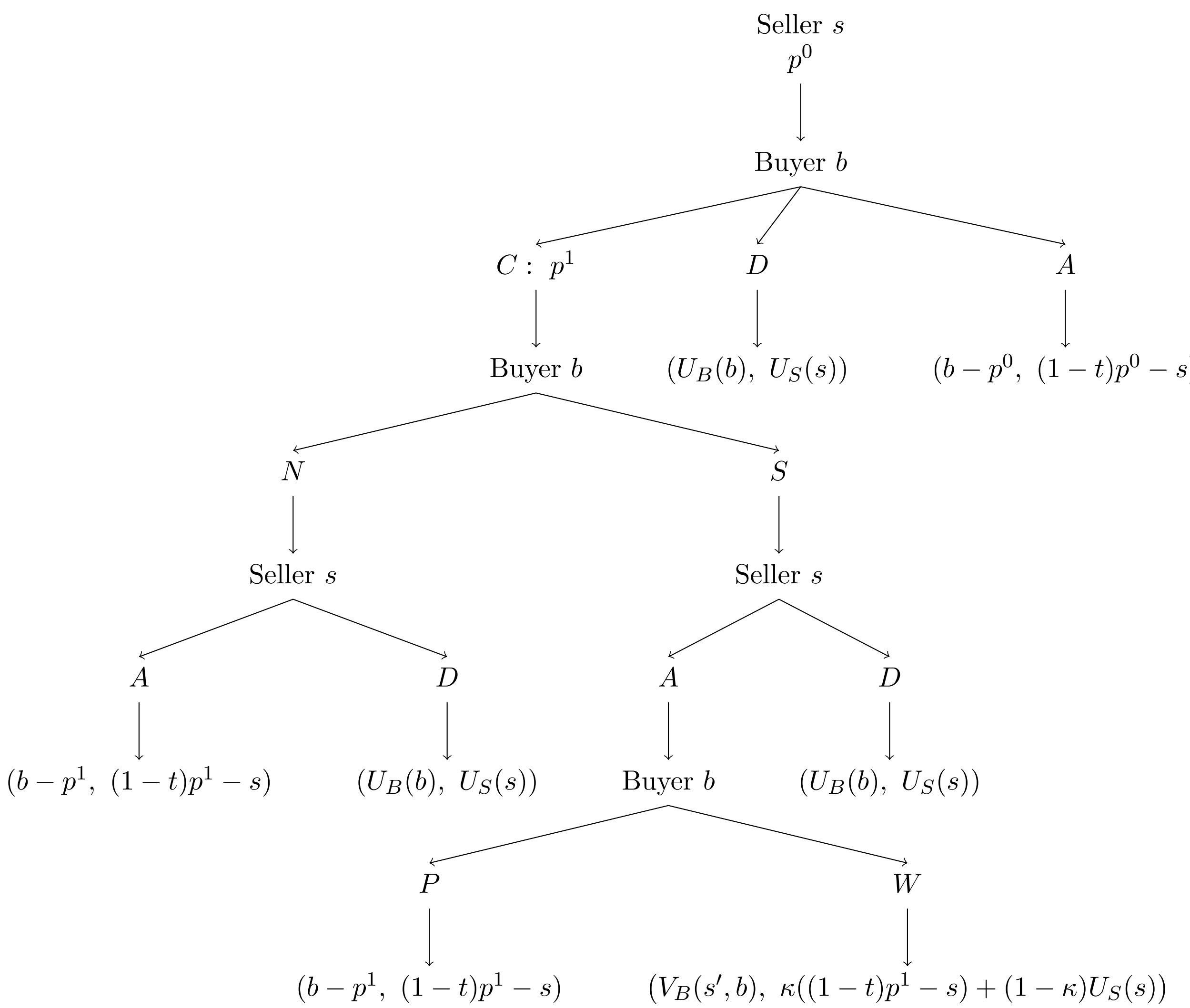

Figure 2: Sequence of events

Note: Decision nodes are labeled by the acting player. Terminal nodes report the buyer payoff first and the seller payoff second, both undiscounted. Stochastic arrival processes and valuation draws by Nature are suppressed.

That is, the total rate at which sellers meet buyers equals the total rate at which buyers meet sellers. In addition, I impose the following condition:

Assumption 1 (Monotonicity and Lipschitz)**.** *The buyer continuation value $V_B(s,b)$ is decreasing in s. Moreover, $V_B(s,\cdot)$ and $V_S(\cdot,b)$ are Lipschitz continuous with Lipschitz constant one.*

Assumption 2 (Indifference)**.** *Whenever a seller is indifferent between choosing A and D in response to a buyer's counteroffer p^1, the seller chooses A.*

Given these assumptions, I solve for the equilibrium using backward induction. A buyer b whose p^1 was accepted and matched to a new seller s' walks away if, and only if, $V_B(s',b) \geq b - p^1$. Given the monotonicity Assumption 1, this can be equivalently stated as $s' \leq s^*(b,p^1)$ where s^* is implicitly defined as $V_B(s^*,b) = b - p^1$. As such, before matching with the new seller, the probability that buyer b walks away is $F_S(s^*(b,p^1))$.

Given Assumption 2, the seller accepts p^1 when his expected payoff from accepting it weakly exceeds that from declining it. In case the buyer chooses to search, such p^1 satisfies

$$\frac{\lambda_B}{\lambda_B + r}\Big((1-\kappa)F_S\big(s^*(b,p^1)\big)\,U_S(s) + \Big[1-(1-\kappa)F_S\big(s^*(b,p^1)\big)\Big]\,\big((1-t)p^1 - s\big)\Big) \;\geq\; U_S(s). \quad (2)$$

Notice that the probability of a walkaway is scaled down by $1-\kappa$, reflecting the fact that even when the buyer walks away, the seller may still be able to trade at price p^1 with another buyer, with an exogenously given probability κ. Let $p^1_S(s,b)$ denote the smallest p^1 that satisfies the seller acceptance condition (2) with equality. Although no closed form expression is available for $p^1_S(s,b)$, the following proposition establishes its existence provided that the continuation value is positive.

Proposition 1. *Suppose $U_S(s) > 0$. Then for any s and b, there exists $p^1_S(s,b)$ satisfying (2) with equality.*

Proof. See Appendix A.1. □

In case the buyer chooses not to search, p^1 should satisfy

$$\frac{\lambda_R}{\lambda_R + r}\Big((1-t)p^1 - s\Big) \;\geq\; U_S(s) \quad (3)$$

Let $p^1_N(s)$ denote the p^1 that satisfies above with equality, which is:

$$p^1_N(s) = \frac{1}{1-t}\left[s + \frac{\lambda_R + r}{\lambda_R}\, U_S(s)\right] \tag{4}$$

The following is the first key prediction of the model:

Proposition 2 (Commitment premium)**.** $p^1_S(s,b) > p^1_N(s)$.

Proof. See Appendix A.1. □

The intuition for this is that a buyer who chooses to search needs to compensate for its own risk of walking away for the seller to accept her counteroffer.

I refer to the buyer action of choosing C, S, and submitting a counteroffer $p^1_S(s,b)$ as making a *noncommitted* counteroffer, labeled CS. Likewise, choosing C, N, and submitting a counteroffer $p^1_N(s)$ is referred to as making a *committed* counteroffer, labeled CN. In either case, submitting any counteroffer below the stated amount leads the seller to choose D after a stochastic delay governed by rate λ_R, in which case the buyer receives continuation value $U_B(b)$. This payoff coincides with that obtained when the buyer chooses D upon matching. Accordingly, I relabel the outcome in which the buyer chooses C and is declined by the seller, regardless of the search choice, as action D. Given this relabeling, buyer actions upon matching with seller s can be summarized as one of $\{A, CN, CS, D\}$. Let $V_B(s,b;\chi,p^0)$ denote buyer b's continuation value conditional on matching with seller s posting initial offer p^0 and taking action $\chi \in \{A, CN, CS, D\}$. Then $V_B(s,b;\chi,p^0)$ is given by:

$$V_B(s,b;\chi,p^0) = \begin{cases} b - p^0 & \text{if } \chi = A, \\ \left(\dfrac{\lambda_R}{\lambda_R + r}\right)^2 \Big(b - p^1_N(s)\Big) & \text{if } \chi = CN, \\ \dfrac{\lambda_B}{\lambda_B + r} \displaystyle\int \max\Big\{b - p^1_S(s,b),\ V_B(s',b)\Big\}\, dF_S(s') - \dfrac{c}{\lambda_B + r} & \text{if } \chi = CS, \\ \dfrac{\lambda_R}{\lambda_R + r}\, U_B(b) & \text{if } \chi = D. \end{cases} \tag{5}$$

To establish the second main prediction of the model, I impose the following regularity condition, which ensures that the noncommitted counteroffer $p^1_S(s,b)$ does not decrease too steeply with the buyer valuation b.

Assumption 3 (Regularity)**.** *For all* (s,b),

$$\Big(1 - F_S\Big(s^*(b, p_S^1(s,b))\Big)\Big)\frac{H_b\Big(b, p_S^1(s,b)\Big)}{H_{p^1}\Big(b, p_S^1(s,b)\Big)} < \frac{\delta_R^2}{\delta_B} - 1, \tag{6}$$

where

$$H_b(b,p^1) = \delta_B\,(1-\kappa)\,f_S\Big(s^*(b,p^1)\Big)\,\frac{\partial s^*(b,p^1)}{\partial b}\,\Big(U_S(s) - (1-t)p^1 + s\Big),$$

and

$$\begin{aligned} H_{p^1}(b,p^1) = \delta_B\Big[&(1-t)\Big(1-(1-\kappa)F_S\Big(s^*(b,p^1)\Big)\Big) \\ &+ (1-\kappa)\,f_S\Big(s^*(b,p^1)\Big)\,\frac{\partial s^*(b,p^1)}{\partial p^1}\,\Big(U_S(s) - (1-t)p^1 + s\Big)\Big]. \end{aligned} \tag{7}$$

Here

$$\delta_R = \frac{\lambda_R}{\lambda_R + r}, \qquad \delta_B = \frac{\lambda_B}{\lambda_B + r},$$

and $s^*(b,p^1)$ *is defined by the cutoff condition* $V_B\Big(s^*(b,p^1), b\Big) = b - p^1$.

The ratio H_b/H_{p^1} captures the negative of the sensitivity of the noncommitted counteroffer $p_S^1(s,b)$ with respect to the buyer valuation b, as implied by the implicit function theorem applied to the seller acceptance condition (2). The left-hand side of (6) can therefore be interpreted as the discounted marginal benefit, from a marginal increase in b, of having a lower noncommitted offer accepted and not walking away. The condition requires that this marginal benefit not exceed the right-hand side of (6), which reflects the heavier discounting faced by noncommitted buyers.

Then the following proposition shows that the model gives rise to an endogenous self selection into commitment status:

Proposition 3 (Self selection into commitment status)**.** *Fix* s*. Let* $\mathcal{M}(s) \subseteq \{D, CS, CN, A\}$ *be the (nonempty) set of actions that are optimal for some* b*. Then, as* b *increases, the buyer's optimal action moves weakly upward in the order* $D \prec CS \prec CN \prec A$ *restricted to* $\mathcal{M}(s)$*.*

Proof. See Appendix A.1. ☐

The key intuition is as follows. Given a seller, buyers with the highest valuation have the highest opportunity cost of entering a time consuming price negotiation or search. They choose to purchase the product at face value. Those with the lowest valuation rather choose to find even lower valuation seller, without entering any price negotiation. Those in the middle send a counteroffer, but among them, those with relatively higher valuation has higher opportunity cost of waiting for the new arrival of a new seller, and as such, they chose not to search. Those with relatively lower valuation choose to search, and are thus non committed. I denote $\chi_B(s,b) \in \{A, CN, CS, D\}$ as the optimal action buyer b takes upon match with seller s.

Finally, turning to the seller's choice of optimal list price $p^0(s)$, first note that seller s's continuation value conditional on matching with a buyer b and choosing list price p^0 is:

$$V_S(s,b;p^0) = \begin{cases} (1-t)p^0 - s & \text{if } \chi_B(s,b;p^0) = A, \\ \dfrac{\lambda_R}{\lambda_R + r} U_S(s) & \text{if } \chi_B(s,b;p^0) \in \{CN, CS\}, \\ U_S(s) & \text{if } \chi_B(s,b;p^0) = D. \end{cases}$$

Integrating the above, the seller chooses p^0 to maximize:

$$\begin{aligned} U_S(s) = \max_{p^0} \Bigg\{ \frac{\lambda_S}{\lambda_S + r} \Bigg[& \mathbb{P}\Big(\chi_B(s,b;p^0) = A \mid s\Big)\Big((1-t)p^0 - s\Big) \\ & + \mathbb{P}\Big(\chi_B(s,b;p^0) \in \{CN, CS\} \mid s\Big) \frac{\lambda_R}{\lambda_R + r} U_S(s) \\ & + \mathbb{P}\Big(\chi_B(s,b;p^0) = D \mid s\Big) U_S(s) \Bigg] \Bigg\}. \end{aligned} \tag{8}$$

I denote the seller's optimal list price by $p^0(s)$.

I discuss two monotonicity results that aid the identification and estimation strategy. The first concerns the list price $p^0(s)$, which plays a central role in the estimation. Its monotonicity allows me to replace the latent seller type s with the observable list price p^0 as the conditioning variable.

Proposition 4 (Monotone list pricing)**.** *Fix s and suppose $\mathcal{M}(s)$ contains A, CN, and D.*

Then the seller's optimal list price $p^0(s)$ is weakly increasing in s.

Proof. See Appendix A.1. $\square$

The second concerns the noncommitted counteroffer $p^1_S(s,b)$ with respect to the buyer type b, and is used to identify the search cost c. To establish this result, I impose a second regularity condition that delivers the monotonicity in Proposition 5.

Assumption 4 (Regularity)**.** *For all (s,b) such that the noncommitted counteroffer $p^1_S(s,b)$ exists, is interior, and differentiable,*

$$H_{p^1}\Big(b, p^1_S(s,b)\Big) > 0,$$

where $H(b,p^1)$ is defined in (7).

The first component of the derivative (7) is positive, reflecting the higher surplus conditional on trade as the counteroffer rises. The second component is negative, reflecting the increased probability that the buyer walks away as the counteroffer rises. Assumption 4 requires that the former effect dominates the latter. This yields the following monotonicity result.

Proposition 5. *The noncommitted counteroffer satisfies*

$$\frac{\partial p^1_S}{\partial b}(s,b) < 0.$$

Proof. See Appendix A.1. $\square$

5 Data

I use an anonymized dataset obtained from Mercari. The dataset includes, for each item, an anonymized item identifier, anonymized seller and buyer identifiers, the item title and description, the item category, and the item condition (unused, almost unused, no noticeable scratches or stains, some scratches or stains, scratches or stains present, overall condition is poor), as well as shipping conditions (shipping time in days, prefecture of origin, shipping method, and shipping payment responsibility, either prepaid by the seller or paid on delivery).

In addition, for each item, the dataset contains a complete timeline of events that records which anonymized user performed which action, including listing the item, liking the item, posting a comment, changing the price, or purchasing the item, and the corresponding timestamp. Details on the construction of the dataset are provided in Online Appendix B.

In line with the homogeneous-good model, I focus on a single product category: the iPhone 7 (128GB). This market definition is similar to those adopted in, for example, Adachi (2016), Hendricks and Sorensen (2018), and Backus and Lewis (2025). I further restrict the sample to items with the following condition categories: no noticeable scratches or stains, some scratches or stains, and scratches or stains present. This leaves me with 12,451 items listed between June 24, 2020 and December 30th, 2021.

I extract offer amounts from buyer comments. Because sellers may adjust prices independently of buyer interaction, I define the effective list price as the posted price after any price changes that occur prior to the first buyer offer. An *observable match* is defined as the arrival of a distinct buyer through a non seller comment or a purchase. There may also be an unobservable match in which a buyer arrives without making a purchase or leaving a comment. Such cases, in which the buyer choice of D is not observed, are accounted for in the estimation. At the observable match level, an offer is classified as accepted if the seller subsequently updates the posted price to the offered amount. Matches are labeled as C if an offer is accepted, A if the item is sold without any offer, and D otherwise. For matches with an accepted offer, I define a walkaway indicator that equals one if the offering buyer does not complete the purchase.

To align the data with the homogeneous goods assumption, I control for observable within market heterogeneity by estimating a hedonic price regression of list prices on observed item characteristics. I then residualize both list prices and offer amounts by subtracting the predicted component from this regression and adding back the intercept, so that prices are expressed net of observable characteristics. The corresponding regression results are reported in Appendix A.2.

Table 2 reports summary statistics at the listing level using residualized prices. Nearly all items are eventually sold, which is consistent with the implications of the model. About 20% of items are sold through bargaining, indicating that bargaining is prevalent in this market.

On average, sellers match with 1.578 buyers per item, implying that sellers have a positive continuation value during negotiations. Table 3 reports summary statistics at the match level. Buyer reneging is strikingly common, occurring in 37.4% of matches on average.

Table 2: Item-level summary statistics

	Mean	SD	Min	Max
List price	14493.63	2817.51	7215.07	23193.62
Sold	0.99	0.09	0.00	1.00
Sold with bargaining	0.20	0.40	0.00	1.00
Received an offer	0.39	0.49	0.00	1.00
Number of observable matches	1.57	1.07	0.00	16.00
Sale price	13995.68	2772.25	2561.87	23175.51
Sale price / list price	0.97	0.06	0.17	1.00
Time to sell (days)	19.38	50.09	0.00	1428.64
Time to first match (days)	15.95	40.06	0.00	373.91
Observations	12451			

Notes: The unit of observation is a listing. List and sales prices are residualized using the hedonic regression described in the main text. An observable match is defined as the arrival of a distinct buyer through a non seller comment or a purchase. Sold with bargaining indicates items that sell in a bargaining match (C) without walkaway. Received an offer indicates items with at least one observed offer. Time to sell is reported only for sold items. Time to first match is reported only for items with at least one buyer match.

The data exhibit patterns that support the remaining model assumptions. Among users who make at least one purchase, 91.4% purchase only one product, and 95.2% of sellers list only one product, supporting the unit transaction assumption. In addition, only 7.2% of listings involve a buyer who reappears through a comment or a purchase after the arrival of another buyer, supporting the assumption that there are no multiple simultaneous buyer arrivals.

6 Preliminary Evidence

A key prediction of the model is that buyers self-select into commitment status. High valuation buyers commit to transacting with the current seller, while lower valuation buyers continue to search while bargaining (Proposition 3). In the data, such commitment can manifest as buyers signaling seriousness by pledging immediate payment. Figure 3 illustrates this behavior using a word cloud constructed from adverbs used in buyer messages during price

Table 3: Observable match-level summary statistics

	Mean	SD	Min	Max
Purchased at list price (A)	0.473	0.499	0.000	1.000
An offer was made and accepted (C)	0.200	0.400	0.000	1.000
Neither of the two above (D)	0.327	0.469	0.000	1.000
An offer was made	0.320	0.466	0.000	1.000
An offer was accepted but not purchased (W)	0.374	0.484	0.000	1.000
Time to purchase after acceptance (days)	3.208	19.400	0.000	647.701
Observations	19525			

Notes: The unit of observation is an observable match. An observable match is defined as the arrival of a distinct buyer through a non seller comment or a purchase. Offer and list prices are residualized using the hedonic regression described in the text. Acceptance (C) refers to matches in which an offer is accepted by the seller. Walkaway (W) is defined only for accepted offer matches (C) and indicates that the original offer maker does not complete the purchase. Time to purchase after acceptance is measured for accepted offer matches (C) as the time from the acceptance event to the first subsequent sale of the item, regardless of whether the original buyer completes the purchase or a different buyer does so in a later match.

negotiations, where language associated with immediacy, such as “soon” and “immediate”, appears frequently. I collect 20 expressions related to immediacy and classify a buyer as making a pledge of *immediate payment* if any of these expressions appears in the negotiation messages (see Online Appendix B for the list). Overall, expressions indicating immediate payment appear in 41.4% of buyer offer messages, suggesting that verbal commitment through payment timing is common in practice.

One might argue that pledges of immediate payment are merely cheap talk and do not reflect true commitment. Table 4 evaluates this claim using OLS regressions that relate bargaining outcomes to price concessions and commitment language in buyer messages. The independent variables include the discount, defined as the difference between the list price and the offer amount divided by the list price, and an indicator for whether the buyer pledged immediate payment in the offer message. The dependent variable is an acceptance indicator in column 1, a walkaway indicator in column 2, and $\log(1 + \text{purchase time})$ in column 3, where time is measured in days. Column 1 uses 5,913 observed matches in which the buyer made an offer. Column 2 restricts attention to the 3,901 matches in which the offer was accepted, and column 3 further restricts to the 3,880 matches in which the product was eventually purchased.

Figure 3: Word Cloud of Adverbs Used in Bargaining Messages

Notes: The figure shows an English word cloud constructed from adverbs appearing in buyer comments during bargaining matches. Japanese comments are tokenized using the Sudachi morphological analyzer. Tokens are filtered to exclude punctuation, single-character kana, and personal names. Japanese lemmas are translated into English using the Open Multilingual WordNet, mapping each Japanese lemma to the first available English lemma. Word sizes are proportional to token frequency, after aggregating frequencies across Japanese words that translate to the same English term and dropping very rare words.

Turning to the results, more aggressive discounts reduce the likelihood of acceptance: a 10 percentage point increase in the discount lowers the acceptance probability by approximately 13.6 percentage points. By contrast, offers accompanied by an immediate payment pledge are 26.8 percentage points more likely to be accepted, holding the discount constant. This acceptance premium is equivalent to an increase of about 19.6% in the allowable discount while holding the acceptance probability fixed, consistent with Proposition 2. Column 2 shows that buyers who pledge immediate payment are 8.9 percentage points less likely to walk away after acceptance. Finally, column 3 shows that, conditional on eventual sale, pledged buyers complete purchases about 14% faster ($\exp(-0.152) - 1$). Together, these results indicate that pledges of immediate payment reduce reneging and post agreement delay and are therefore typically honored in practice.

Table 4: Commitment Premium, Walkaway, and Time to Purchase

	Accepted	Walkaway	$\log(1 + \text{time to purchase})$
Constant	0.482	0.348	0.476
	(0.009)	(0.013)	(0.023)
Discount	-1.365	0.967	2.231
	(0.075)	(0.126)	(0.228)
Commit	0.268	-0.089	-0.162
	(0.014)	(0.016)	(0.028)
Observations	5913	3901	3880
R^2	0.114	0.023	0.032
Adjusted R^2	0.114	0.022	0.031

Notes: The unit of observation is an observable match, using the first offer in each match. Column 1 is a linear probability model for acceptance. The sample consists of observable matches in which the buyer makes an offer (C or D). Column 2 is a linear probability model for walkaway. The sample consists of accepted offer matches (C only). Column 3 regresses $\log(1 + \text{time to purchase})$, where time is measured in days. The sample consists of accepted offer matches (C) that are eventually purchased. The discount is defined as $(p_0 - p_o)/p_0$, where p_0 is the residualized list price and p_o is the residualized offer amount. All prices are residualized using the hedonic regression described in the main text.

7 Identification and Estimation

My objective is to estimate the following model primitives: the arrival rate of buyers to sellers (λ_S), the arrival rate of sellers to buyers (λ_B), the arrival rate of purchase opportunities following a counteroffer (λ_R), the seller valuation distribution F_S, the buyer valuation distribution F_B, and the buyer search cost c, for a given discount rate r, numbers of buyers and sellers N_B and N_S, and an exogenous post walkaway trading rate κ. Identification proceeds in stages. Arrival rates are identified from observed buyer arrivals and post counteroffer purchase delays. Seller and buyer valuation distributions are recovered from optimality and indifference conditions that map observed prices into latent valuations. The search cost is then identified from the indifference between searching and not searching. I describe estimation procedures that directly implement these constructive identification arguments.

For the discount rate r, I report results based on values implied by the daily discrete discount factors used in Bodoh-Creed et al. (2021). I convert these into continuous daily discount rates using $\delta = e^{-r}$, yielding rates ranging from 0.02 to 0.29. Although these rates may appear high when interpreted as pure time discounting, they are best understood as effective discounting that captures both time preferences and the risk of exit from the market.

The number of buyers N_B and the number of sellers N_S are defined as the number of unique buyers who complete a purchase and the number of listings observed over the sample period, respectively. The exogenous post walkaway trading rate κ is calibrated as the fraction of products that are purchased by another buyer within 1.5 days after a noncommitted offer by the original buyer, conditional on no purchase by that buyer, which equals 0.687.

Throughout the estimation, I recover conditional expectations of the form $\mathbb{E}[Y \mid s]$ by exploiting the monotonicity of the seller posting rule $p_0(s)$ (Proposition 4). Specifically, whenever a conditional expectation is indexed by the seller type s, I replace s with the observable residualized list price $p_0(s)$ and estimate $\mathbb{E}[Y \mid s]$ instead. These conditional expectations are estimated using nonparametric local linear regression with a Gaussian kernel. The bandwidth is chosen according to a normal reference rule of thumb, $h = 1.06\, \hat{\sigma}_{p_0}\, n^{-1/5}$, where $\hat{\sigma}_{p_0}$ is the sample standard deviation of p_0 and n is the sample size. This approach delivers smooth and stable estimates of conditional expectations while mitigating boundary bias near the edges of the support.

Arrival rates λ_S and λ_B. I assume that the number of unobservable matches is equal to the number of pure likes, that is, likes not accompanied by a purchase or a comment. The seller arrival rate λ_S is then identified as the expected number of distinct buyer arrivals divided by the number of days elapsed from listing to sale, with exposure capped at 30 days to limit the influence of extremely long lived listings. I set N_S equal to the number of distinct users who list at least one item, and N_B equal to the number of distinct users who complete at least one purchase as a buyer, during the sample period. The buyer arrival rate λ_B is then recovered from the steady state condition (1).

Response rate λ_R. The response rate λ_R is identified from the time between a committed counteroffer and the subsequent purchase. In the data, I restrict attention to committed counteroffers that do not result in walkaway, and observe for each such match the elapsed time between the counteroffer timestamp and the sale timestamp. In the model, this delay reflects two sequential arrivals governed by the same rate λ_R, implying an expected delay of $2/\lambda_R$. I therefore identify λ_R by equating this mean to the sample mean of the observed delays.

Seller Valuation Distribution F_S. F_S is identified from (4), which expresses $p_N^1(s)$ in terms of s and $U_S(s)$. Note that the continuation value can also be expressed as expected discounted realized payoff:

$$U_S(s) = \mathbb{E}\Big[e^{-rT_{sell}}\Big((1-t)p_{sell} - s\Big) \;\Big|\; s\Big] \tag{9}$$

where T_{sell} and p_{sell} are random variables representing the days since listing seller s sells his product and its price, respectively. Solving for s from (4) and (9), we obtain an expression for s:

$$s = \frac{\mathbb{E}\Big[e^{-rT_{\text{sell}}}(1-t)p_{\text{sell}} - \frac{\lambda_R}{\lambda_R+r}(1-t)p_N^1(s) \;\Big|\; s\Big]}{\mathbb{E}\Big[e^{-rT_{\text{sell}}} \;\Big|\; s\Big] - \frac{\lambda_R}{\lambda_R+r}} \tag{10}$$

F_S is thus identified as the empirical cumulative distribution function of these pseudovalues.

Buyer Valuation Distribution F_B. The buyer valuation distribution F_B is identified from the indifference condition between immediate acceptance and making a committed counteroffer (Proposition 3). The proof in Appendix A.1 shows that, for a given seller type s, the valuation of the indifferent buyer, denoted by $\tau^{AC}(s)$, satisfies

$$\tau^{AC}(s) = \frac{p^0(s) - \left(\frac{\lambda_R}{\lambda_R+r}\right)^2 p_N^1(s)}{1 - \left(\frac{\lambda_R}{\lambda_R+r}\right)^2}.$$

The left tail of the buyer valuation distribution at $\tau^{AC}(s)$ is also identified:

$$F_B\Big(\tau^{AC}(s)\Big) = 1 - \mathbb{E}\Big[\mathbb{I}\Big\{\chi_B(s,b) = A\Big\} \;\Big|\; s\Big].$$

The expectation on the right hand side represents, for a given seller s, the probability that an arriving buyer immediately purchases the product (action A). In the data, this expectation is first estimated conditional on s and on the match being observable. I then recover the corresponding unconditional probability by correcting for selection into observability using the seller arrival rate λ_S and the implied probability that a buyer arrival generates an observable match. Details of this correction are provided in Appendix A.3.

Because I only observe $\tau^{AC}(s)$ over a limited range, F_B is nonparametrically identified only on a restricted support. I therefore parametrize F_B as a normal distribution with mean μ_B and variance σ_B^2. I estimate μ_B and σ_B^2 by least squares:

$$(\hat{\mu}_B, \hat{\sigma}_B^2) = \arg\min_{\mu_B, \sigma_B^2} \sum_{s \in \mathcal{S}} \left[\left(1 - \hat{\mathbb{E}}\Big[\mathbb{I}\{\chi_B(s,b) = A\} \;\Big|\; p^0(s) \Big] \right) - \Phi\Big(\tau^{AC}(s) \,;\, \mu_B, \sigma_B^2 \Big) \right]^2$$

where $\mathcal{S}$ is the set of sellers in the sample, $\hat{\mathbb{E}}\Big[\cdot \;\Big|\; \cdot\Big]$ denotes the estimated conditional expectation, and Φ is the cumulative distribution function of a normal.

Search Cost c. Finally, the search cost c is identified using the indifference condition between searching and not searching. For a given seller s, the valuation of a buyer who is indifferent between searching and not searching is identified, since the fraction of buyers below this threshold equals the fraction of buyers who choose either CS or D, as shown in Proposition 3.

$$\tau^{NS}(s) = F_b^{-1}\left(\mathbb{E}\Big[\mathbb{I}\Big\{\chi_B(s,b) \in \{CS, D\}\Big\} \;\Big|\; s \Big] \right)$$

Such buyer should satisfy $V_B(s,b,CN;p^0) = V_B(s,b,CS;p^0)$, or,

$$\left(\frac{\lambda_R}{\lambda_R + r}\right)^2 \Big(\tau^{NS}(s) - p_N^1(s)\Big) = \mathbb{E}\left[e^{-rT_{purchase}} \Big(\tau^{NS}(s) - p_{\text{purchase}}\Big) - \int_0^{T_{purchase}} e^{-rT_{purchase}}\, c\, dt \;\Big|\; s \right]$$

where I have expressed $V_B(s,b,CS)$ in terms of expected discounted payoff, and random variables $T_{purchase}$ and $p_{purchase}$ are time since the current match until purchasing of a product, and its purchase price, respectively. Integrating the above with respect to s and solving for c yields:

$$c = r\, \frac{\int \mathbb{E}\Big[e^{-rT_{purchase}} \Big(\tau^{NS}(s) - p_{purchase}\Big) \;\Big|\; s \Big]\, dF_S(s) \;-\; \int \left(\frac{\lambda_R}{\lambda_R + r}\right)^2 \Big(\tau^{NS}(s) - p_N^1(s)\Big)\, dF_S(s)}{\int \mathbb{E}\Big[1 - e^{-rT_{purchase}} \;\Big|\; s \Big]\, dF_S(s)} \tag{11}$$

To estimate the right hand side, I recover the purchase price $p^{purchase}$ and the time to purchase $T^{purchase}$ for the buyer with valuation $\tau^{NS}(s)$. Proposition 3 implies that this buyer has the highest valuation among buyers matched to seller s and chooses CS. The monotonicity result in Proposition 5 implies that the buyer with valuation $\tau^{NS}(s)$ corresponds to the buyer who makes the lowest noncommitted counteroffer $p_S^1(s,b)$ for a given s. I discretize the list price into 50 bins and, within each bin, retain observations whose noncommitted offers fall between the 0.001 and 0.05 quantiles. Conditional expectations are estimated using this subsample, and integrals are computed by numerical integration using the empirical distribution of list prices.

8 Results

Estimation results for different values of r are reported in Table 5. Panel A reports parameters that are not estimated, either calibrated or directly observed, while Panel B reports estimates for parameters that are invariant across specifications. The estimated response rate is $\lambda_R = 3.51$, implying that a response or purchase opportunity arrives on average once every 6.83 hours. The buyer arrival rate to a seller is estimated to be $\lambda_S = 0.61$, meaning that a seller encounters a buyer approximately once every 1.65 days, which is substantially slower than the response rate. Conversely, the seller arrival rate to a buyer is $\lambda_B = 0.68$, reflecting the fact that sellers are relatively more abundant than buyers in the market, so buyers encounter sellers more frequently than sellers encounter buyers.

Turning to Panel C, which reports estimates that vary with r, the implied search cost is economically nonnegligible. At the benchmark value $r = 0.05$, the estimated flow search cost is 1,478 yen per day, about 10.2% of the median buyer valuation. Estimates of the search cost increase monotonically with r, both in absolute terms and relative to buyer valuations. The remaining columns report quartiles of the seller and buyer valuation distributions. For low values of r up to 0.07, buyer valuations exceed seller valuations at the median and upper quartiles, implying that most matches exhibit gains from trade in a static sense. Even in the complete-information environment of the model, agents' continuation values from matching with alternative partners provide a reason why trade does not always occur despite the presence of gains from trade.

In terms of model fit, $r = 0.05$ produces the best match to the distribution of list prices.

Although list prices are not targeted moments in the estimation, the model reproduces their empirical distribution reasonably well at this value. Simulating the equilibrium using the estimated parameters (see Online Appendix C for details) yields a mean list price of 14,493.6 yen in the data versus 14,824.1 yen in the model and a median of 14,145.8 yen in the data versus 15,075.4 yen in the model. The model understates dispersion, with a standard deviation of 2,817.5 yen in the data compared with 1,638.9 yen in the model, and compresses the upper tail of the distribution. I therefore use $r = 0.05$ as the benchmark value for the counterfactual analysis.

Table 5: Structural estimates across discount rates

Panel A: Calibrated parameters

N_S	N_B	κ
4545	4056	0.687

Panel B: Estimated parameters invariant to r

λ_R	λ_S	λ_B
3.513	0.605	0.678

Panel C: Parameters varying with r

		F_S			F_B		
r	c	Q1	Q2	Q3	Q1	Q2	Q3
0.020	1385.324	5647.55	6648.86	7268.06	-57957.22	26465.32	122268.08
0.050	1478.432	7570.95	8740.62	9854.90	-22178.11	14443.64	56002.04
0.070	1538.512	8007.85	9200.57	10392.96	-15392.77	12136.85	43377.49
0.120	1682.101	8526.88	9737.67	11005.00	-8366.50	9710.28	30223.81
0.140	1737.015	8643.38	9857.04	11139.14	-6972.21	9218.80	27592.38
0.210	1918.685	8897.24	10116.24	11428.20	-4205.23	8223.86	22328.41
0.290	2107.961	9054.33	10276.27	11606.21	-2698.94	7663.91	19423.67

Notes: This table reports structural parameter values for different values of the discount rate r. Panel A reports parameters that are not estimated, either calibrated or directly observed. Panel B reports estimated parameters that are invariant across specifications. Panel C reports parameters that vary with r. In Panel C, the column labeled c reports the estimated flow search cost, and columns labeled F_S and F_B report the first, second, and third quartiles of the seller and buyer valuation distributions, respectively.

9 Counterfactual Analysis

Using the estimated model, I conduct a counterfactual experiment in which buyers are fully committed to purchasing once their offers are accepted. I implement this scenario by imposing an effectively infinite search cost during the bargaining stage, thereby eliminating post acceptance search. Under this full commitment policy, buyers must complete the purchase after an offer is accepted and cannot search for other sellers. The search cost faced by unmatched buyers is held fixed, so only search during the bargaining stage is shut down. I compute the stationary equilibrium by value function iteration on U_S, U_B, and V_B. Details of the simulation procedure are provided in Online Appendix C.

I measure the welfare of a seller with valuation s by $U_S(s)$ and the welfare of a buyer with valuation b by $U_B(b)$. Platform welfare is measured by expected commission revenue. I first compute the expected discounted commission from a match between seller s and buyer b:

$$\begin{aligned} V_p(s,b) = t\Bigg[& \mathbb{P}(\chi_B(s,b) = A)\ p^0(s) \\ & + \mathbb{P}(\chi_B(s,b) = CN)\ \frac{\lambda_R}{\lambda_R + r}\, p_N^1(s) \\ & + \mathbb{P}(\chi_B(s,b) = CS)\ \frac{\lambda_B}{\lambda_B + r}\left[1 - (1-\kappa)\, F_S\Big(s^*(b, p_S^1(s,b))\Big)\right] p_S^1(s,b)\Bigg]. \end{aligned} \tag{12}$$

Overall welfare is measured on a per listing basis as the sum of expected seller welfare, buyer welfare scaled by the buyer to seller ratio, and platform welfare per seller:

$$W = \int U_s(s)\, dF_s(s) + \frac{N_b}{N_s}\int U_b(b)\, dF_b(b) + \int\int V_p(s,b)\, dF_s(s)\, dF_b(b). \tag{13}$$

Table 6 reports the aggregate welfare effects of introducing a full commitment policy based on the aforementioned welfare measures. Overall, total welfare decreases modestly, with a loss of 20.2 yen per listing. Sellers gain on average 55.2 yen per listing, while buyers lose 59.1 yen on average. Platform revenue also declines by 22.7 yen per listing. The table further reports heterogeneous welfare effects by valuation quartiles for sellers and buyers, and the magnitude of these impacts varies substantially across types. Seller welfare effects are positive throughout the distribution and strongly increasing in seller valuation: gains are modest in

	Baseline	Full commitment	Difference
Total welfare	14432.66	14412.50	-20.16
Sellers			
Overall	3284.66	3339.87	55.21
Q1	3434.54	3452.15	17.61
Q2	3338.29	3355.81	17.51
Q3	3188.48	3268.72	80.24
Q4	2863.41	3046.30	182.89
Buyers			
Overall	11603.69	11544.64	-59.05
Q1	-20522.94	-20558.35	-35.41
Q2	-1026.40	-1065.34	-38.94
Q3	37900.36	37820.28	-80.09
Q4	88915.82	88816.93	-98.89
Platform			
Overall	792.76	770.09	-22.67

Table 6: Welfare under baseline and full commitment

Notes: Welfare is measured on a per listing basis. Seller welfare is given by $U_S(s)$, buyer welfare by $U_B(b)$, and platform welfare by expected commission revenue $V_p(s,b)$; see (12). Overall welfare is defined in (13). Rows labeled "Overall" report welfare averaged over the full seller and buyer valuation distributions. Rows labeled Qk report welfare averaged over agents whose valuations lie in the k-th quartile of the relevant distribution, holding the distribution of the opposing side fixed. Differences are computed as Full commitment minus Baseline.

the first two quartiles, at 17.6 yen in the first quartile and 17.5 yen in the second quartile, but rise to 80.2 yen in the third quartile and 182.9 yen in the top quartile. Buyer welfare effects, by contrast, are uniformly negative across the distribution, with losses increasing in buyer valuation. Buyers in the bottom quartile incur a loss of 35.4 yen, compared with losses of 38.9 yen, 80.1 yen, and 98.9 yen in the second, third, and fourth quartiles, respectively.

To understand the internal mechanism behind these results, Table 7 reports the fractions of each buyer action $\chi_B(s,b) \in \{A, C, D\}$, along with list prices p^0 and accepted counteroffers p^1, both overall and by quartiles of the seller valuation s, as well as their changes under the counterfactual. Overall, the introduction of full commitment reduces counteroffers ($\Delta C = -0.020$) and increases outright declines ($\Delta D = 0.026$), while slightly reducing immediate purchases. These shifts are accompanied by an increase in list prices ($\Delta p^0 = 105.5$)

and a decline in accepted counteroffer prices ($\Delta p^1 = -176.4$).

The effects are strongly heterogeneous across seller types. Sellers in the top quartile experience a sharp reduction in counteroffers ($\Delta C = -0.050$), with most buyers switching to outright declines ($\Delta D = 0.066$). Because these sellers no longer face delayed purchases and walkaways, their continuation values increase, lowering the opportunity cost of raising list prices and being declined, and they respond by raising list prices substantially ($\Delta p^0 = 301.5$). Sellers with lower valuations are less directly affected, as they face relatively few noncommitted buyers to begin with, but they also raise list prices modestly as higher-valuation sellers raise prices and outside options improve ($\Delta p^0 = 60.3$ in the first and third quartiles, and $\Delta p^0 = 0.0$ in the second quartile). This upward shift in list prices improves their continuation values as well as the committed counteroffers directed toward lower-valuation sellers.

The aggregate effects are driven primarily by changes among higher-valuation sellers. When matched with these sellers, buyers face substantially higher list prices, which is particularly detrimental for higher-valuation buyers, who are more likely to purchase at list prices. In contrast, low-valuation buyers are less affected, as their outcomes are largely determined by whether they can match with lower-valuation sellers. The platform experiences a welfare loss due to both an extensive-margin reduction in trade, reflected in fewer counteroffers and more declines ($\Delta C = -0.020$ and $\Delta D = 0.026$), and an intensive-margin decline in negotiated prices ($\Delta p^1 = -176.4$). These losses outweigh the gains from eliminating walkaways and from higher list prices. Overall, a full commitment policy benefits sellers, but is detrimental to buyers and the platform.

10 Conclusion

This paper is the first to study price negotiations on online marketplaces while explicitly accounting for the fact that buyers naturally search for alternative sellers, which creates a commitment problem in completing payments, a feature that has long been pervasive in practice. I build a structural model of bargaining with buyer search in which buyers self-select into commitment status, and sellers require a premium from non committed buyers when accepting their counteroffers. Using detailed textual data from a Japanese online platform, I

	Baseline					Difference				
	A	C	D	p^0	p^1	ΔA	ΔC	ΔD	Δp^0	Δp^1
Overall	0.261	0.322	0.417	14824.1	13498.3	-0.006	-0.020	0.026	105.5	-176.4
Q1	0.259	0.374	0.368	12884.4	11537.0	-0.008	0.005	0.003	60.3	9.5
Q2	0.272	0.327	0.401	14412.1	13255.3	0.002	-0.016	0.014	0.0	-14.6
Q3	0.255	0.317	0.428	15356.8	14147.2	-0.001	-0.021	0.022	60.3	12.1
Q4	0.258	0.272	0.471	16643.2	15731.1	-0.016	-0.050	0.066	301.5	-384.0

Table 7: Action shares and prices under baseline, with changes under full commitment

Notes: Rows report means overall and by quartiles of the seller valuation s. Action shares are averaged over all buyer types b, with C pooling CN and CS. p^0 denotes the equilibrium list price. For counteroffers, p^1 pools $p^1_N(s)$ for CN outcomes and $p^1_S(s,b)$ for CS outcomes. Difference columns report Full Commitment minus Baseline.

detect buyer attempts to credibly convey immediate payment and show that sellers accept lower counteroffers from such buyers, consistent with the model's predictions.

Counterfactual analysis shows that a full commitment policy can reduce overall welfare. In equilibrium, sellers, especially those with higher valuations, respond by raising their list prices, while the elimination of the option value of search during bargaining further reduces buyer welfare. The platform also experiences a revenue loss through both the extensive margin, due to less frequent counteroffers and more declines, and the intensive margin, due to lower negotiated prices. Although these quantitative results are specific to the institutional setting and estimated primitives in this market, the underlying framework and economic mechanism are applicable to other bargaining environments in which buyers can continue searching while negotiating.

While platforms such as eBay have implemented randomized rollouts of commitment rules, such experiments capture only a limited range of behavior and cannot evaluate platform wide equilibrium effects. This analysis complements those efforts by providing a model based framework for studying platform design choices. At the same time, the framework is simplified and relies on strong assumptions, most notably complete information, which are imposed for tractability and to enable counterfactual analysis. Future work could relax these assumptions by estimating models with incomplete information or richer inter bargaining dynamics, following recent work on static models (see Freyberger and Larsen (2025); Larsen (2021)), though possibly at the cost of a tractable equilibrium.

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A Appendix

A.1 Proofs for Propositions

Proof for Proposition 1. Fix s and b. Under the maintained assumption in Proposition 1, $U_S(s) > 0$. Define $l(p^1) \equiv (1-t)p^1 - s$ and $\delta \equiv \lambda_B/(\lambda_B + r) \in (0,1)$. Let

$$w(p^1) \equiv (1-\kappa)F_S\Big(s^*(b,p^1)\Big), \qquad G(p^1) \equiv \delta\Big(w(p^1)U_S(s) + \big[1-w(p^1)\big]l(p^1)\Big) - U_S(s).$$

By Assumption 1, for each b the function $V_B(\cdot, b)$ is continuous and strictly decreasing in s. Hence for any (b, p^1) the cutoff $s^*(b,p^1)$ defined by $V_B(s^*(b,p^1), b) = b - p^1$ is well defined, and the mapping $p^1 \mapsto s^*(b,p^1)$ is continuous. Since F_S is absolutely continuous, it is continuous, so $w(\cdot)$ is continuous. Because $l(\cdot)$ is linear, $G(\cdot)$ is continuous.

Let $\underline{p}^1 \equiv (U_S(s) + s)/(1-t)$ so that $l(\underline{p}^1) = U_S(s)$. Then

$$G(\underline{p}^1) = \delta\Big(w(\underline{p}^1)U_S(s) + \big[1-w(\underline{p}^1)\big]U_S(s)\Big) - U_S(s) = (\delta-1)U_S(s) < 0.$$

Next, since $0 \le w(p^1) \le 1-\kappa$, we have $1 - w(p^1) \ge \kappa > 0$ for all p^1. Using $U_S(s) > 0$ and $w(p^1) \ge 0$,

$$G(p^1) = \delta\Big(w(p^1)U_S(s) + \big[1-w(p^1)\big]l(p^1)\Big) - U_S(s) \ge \delta\,\kappa\,l(p^1) - U_S(s).$$

Because $l(p^1) = (1-t)p^1 - s$ diverges to $+\infty$ as $p^1 \to \infty$, the right hand side diverges to $+\infty$. Hence there exists $\overline{p}^1$ such that $G(\overline{p}^1) > 0$. By continuity of G, the intermediate value theorem implies that there exists $p^1_S \in (\underline{p}^1, \overline{p}^1)$ with $G(p^1_S) = 0$, that is, (2) holds with equality at p^1_S. □

Proof for Proposition 2. Suppose that $p^1_S(s,b)$ exists in a neighborhood of b. Then the seller acceptance condition (2) holds with equality. Likewise, $p^1_N(s)$ satisfies (3) with equality. Since

$\frac{\lambda_B}{\lambda_B+r} < \frac{\lambda_R}{\lambda_R+r}$, combining the two equalities implies

$$\begin{aligned}(1-\kappa)&F_S\Big(s^*(b,p_S^1(s,b))\Big)\,U_S(s) \\ &+\Big[1-(1-\kappa)F_S\Big(s^*(b,p_S^1(s,b))\Big)\Big]\Big((1-t)p_S^1(s,b)-s\Big) \;>\; (1-t)p_N^1(s)-s.\end{aligned} \tag{14}$$

The left-hand side of (14) is a convex combination of $U_S(s)$ and $(1-t)p_S^1(s,b)-s$, with weight $(1-\kappa)F_S\Big(s^*(b,p_S^1(s,b))\Big) \in [0,1]$ on the former. Since $U_S(s) \le (1-t)p_S^1(s,b)-s$ at the acceptance threshold, the expression is bounded above by $(1-t)p_S^1(s,b)-s$. Therefore,

$$(1-t)p_S^1(s,b)-s \;>\; (1-t)p_N^1(s)-s,$$

which implies

$$p_S^1(s,b) \;>\; p_N^1(s).$$

□

Proof of Proposition 3. Fix s. Define $\delta_R = \frac{\lambda_R}{\lambda_R+r}$ and $\delta_B = \frac{\lambda_B}{\lambda_B+r}$. Let $s^*(b,p^1)$ be defined by $V_B\Big(s^*(b,p^1),b\Big) = b-p^1$. Define the seller acceptance function

$$H(b,p^1) := \delta_B\bigg((1-\kappa)F_S\Big(s^*(b,p^1)\Big)\,U_S(s)+\Big[1-(1-\kappa)F_S\Big(s^*(b,p^1)\Big)\Big]\Big((1-t)p^1-s\Big)\bigg)-U_S(s),$$

so that the noncommitted counteroffer is characterized by $H\Big(b,p_S^1(s,b)\Big)=0$ (see (2)).

Differentiating H yields

$$H_b(b,p^1) = \delta_B(1-\kappa)\,f_S\Big(s^*(b,p^1)\Big)\,\frac{\partial s^*(b,p^1)}{\partial b}\,\Big(U_S(s)-(1-t)p^1+s\Big),$$

and

$$\begin{aligned}H_{p^1}(b,p^1) = \delta_B\Big[&(1-t)\Big(1-(1-\kappa)F_S\Big(s^*(b,p^1)\Big)\Big) \\ &+(1-\kappa)\,f_S\Big(s^*(b,p^1)\Big)\,\frac{\partial s^*(b,p^1)}{\partial p^1}\,\Big(U_S(s)-(1-t)p^1+s\Big)\Big].\end{aligned}$$

Whenever $p_S^1(s,b)$ is interior and differentiable and $H_{p^1} \neq 0$, the implicit function theorem implies

$$\frac{\partial p_S^1(s,b)}{\partial b} = -\frac{H_b\Big(b, p_S^1(s,b)\Big)}{H_{p^1}\Big(b, p_S^1(s,b)\Big)}.$$

Assumption 3 implies

$$\Big(1 - F_S\Big(s^*(b, p_S^1(s,b))\Big)\Big)\Big(-\frac{\partial p_S^1(s,b)}{\partial b}\Big) < \frac{\delta_R^2}{\delta_B} - 1. \tag{15}$$

For immediate purchase,

$$\frac{\partial V_B(s,b;A,p^0)}{\partial b} = 1.$$

For a committed counteroffer,

$$\frac{\partial V_B(s,b;CN,p^0)}{\partial b} = \delta_R^2.$$

For decline,

$$\frac{\partial V_B(s,b;D,p^0)}{\partial b} = \delta_R\,\delta_B \int \frac{\partial V_B(s',b)}{\partial b}\,dF_S(s') \;\leq\; \delta_R\,\delta_B.$$

where the inequality follows from the Lipschitz–1 condition in Assumption 1.

For a noncommitted counteroffer, applying Leibniz' rule yields:

$$\frac{\partial V_B(s,b;CS,p^0)}{\partial b} = \delta_B\left[\int_{-\infty}^{s^*(b,p_S^1)} \frac{\partial V_B(s',b)}{\partial b}\,dF_S(s') + \Big(1 - F_S(s^*(b,p_S^1))\Big)\Big(1 - \frac{\partial p_S^1(s,b)}{\partial b}\Big)\right].$$

By the Lipschitz–1 condition, $\frac{\partial V_B(s',b)}{\partial b} \leq 1$ whenever the derivative exists, hence

$$\int_{-\infty}^{s^*(b,p_S^1)} \frac{\partial V_B(s',b)}{\partial b}\,dF_S(s') \leq F_S\Big(s^*(b,p_S^1)\Big).$$

Therefore,

$$\begin{aligned}\frac{\partial V_B(s,b;CS,p^0)}{\partial b} &\leq \delta_B\Big[F_S(s^*) + (1 - F_S(s^*))\Big(1 - \frac{\partial p_S^1}{\partial b}\Big)\Big] \\ &= \delta_B\Big[1 + (1 - F_S(s^*))\Big(-\frac{\partial p_S^1}{\partial b}\Big)\Big] \\ &< \delta_B\Big[1 + \Big(\frac{\delta_R^2}{\delta_B} - 1\Big)\Big] = \delta_R^2,\end{aligned}$$

where the strict inequality uses (15).

Given $\lambda_B > \lambda_R$, the marginal values satisfy

$$\frac{\partial V_B(s,b;D)}{\partial b} < \frac{\partial V_B(s,b;CS)}{\partial b} < \frac{\partial V_B(s,b;CN)}{\partial b} < \frac{\partial V_B(s,b;A)}{\partial b}$$

It follows that each of the differences

$$V_B(s,b;CS) - V_B(s,b;D), \quad V_B(s,b;CN) - V_B(s,b;CS), \quad V_B(s,b;A) - V_B(s,b;CN)$$

is weakly increasing in b, so each adjacent pair of value functions crosses at most once. Since $\mathcal{M}(s)$ is nonempty, this single-crossing property implies that the buyer's optimal action admits a unique monotone partition of the type space, ordered as $D \prec CS \prec CN \prec A$.

$\square$

Proof of Proposition 4. Fix s. Proposition 3 implies that the buyer behavior can be represented by cutoffs. In particular, there exists a threshold $\tau^{AC}(p^0,s)$ such that buyers choose A if and only if $b \geq \tau^{AC}(p^0,s)$, and choose CN or CS otherwise among buyers who do not choose D. At the A and CN margin, the buyer is indifferent between purchasing immediately and making a committed counteroffer. Thus $\tau^{AC}(p^0,s)$ satisfies

$$\tau^{AC}(p^0,s) - p^0 = \delta_R^2\Big(\tau^{AC}(p^0,s) - p_N^1(s)\Big), \qquad \delta_R = \frac{\lambda_R}{\lambda_R + r}.$$

Solving,

$$\tau^{AC}(p^0,s) = \frac{p^0 - \delta_R^2 p_N^1(s)}{1-\delta_R^2}. \tag{16}$$

Since $p_N^1(s)$ is weakly increasing in s, it follows that $\tau^{AC}(p^0,s)$ is weakly increasing in both p^0 and s. Using the cutoff representation,

$$\mathbb{P}\Big(\chi_B = A \mid s, p^0\Big) = 1 - F_B\Big(\tau^{AC}(p^0,s)\Big),$$
$$\mathbb{P}\Big(\chi_B \in \{CN, CS\} \mid s, p^0\Big) = F_B\Big(\tau^{AC}(p^0,s)\Big) - F_B\Big(\tau^{CD}(s)\Big).$$

Substituting into (8) and dropping the positive factor $\lambda_S/(\lambda_S + r)$, the seller's objective can be written as

$$\Psi(p^0, s) = \Big(1 - F_B(\tau^{AC}(p^0, s))\Big)\Big((1-t)p^0 - s\Big) + F_B(\tau^{AC}(p^0, s))\, \delta_R U_S(s)$$

Fix $p_2 > p_1$ and define $Q(p^0, s) := F_B(\tau^{AC}(p^0, s))$. Then

$$\Psi(p_2, s) - \Psi(p_1, s) = (1-t)(p_2 - p_1) - (1-t)\Big(Q(p_2, s)p_2 - Q(p_1, s)p_1\Big) + \Big(Q(p_2, s) - Q(p_1, s)\Big)\Big(\delta_R U_S(s) + s\Big).$$

Because $\tau^{AC}(p^0, s)$ is weakly increasing in p^0, $Q(p^0, s)$ is weakly increasing in p^0. Moreover, $\delta_R U_S(s) + s$ is weakly increasing in s by Assumption 1. Hence $\Psi(p_2, s) - \Psi(p_1, s)$ is weakly increasing in s, so $\Psi(p^0, s)$ has increasing differences in (p^0, s). By Topkis's monotonicity theorem, the seller's optimal list price $p^0(s)$ is weakly increasing in s. □

Proof of Proposition 5. Fix s and consider (s, b) such that $p_S^1(s, b)$ exists, is interior, and differentiable. Since $p_S^1(s, b)$ solves the acceptance condition (2) with equality, the implicit function theorem implies

$$\frac{\partial p_S^1}{\partial b}(s, b) = -\frac{H_b\Big(b, p_S^1(s, b)\Big)}{H_{p^1}\Big(b, p_S^1(s, b)\Big)}.$$

Assumption 4 gives $H_{p^1}\Big(b, p_S^1(s, b)\Big) > 0$, so it suffices to show $H_b\Big(b, p_S^1(s, b)\Big) > 0$.

By the definition of H_b in Assumption 3,

$$H_b(b, p^1) = \delta_B(1-\kappa)\, f_S\Big(s^*(b, p^1)\Big)\, \frac{\partial s^*(b, p^1)}{\partial b}\, \Big(U_S(s) - (1-t)p^1 + s\Big).$$

All factors except the last two are nonnegative. First, $\frac{\partial s^*(b,p^1)}{\partial b} \geq 0$ follows from Assumption 1: since $V_B(s, b)$ is decreasing in s and Lipschitz in b with constant one, the cutoff defined by $V_B(s^*(b, p^1), b) = b - p^1$ is weakly increasing in b. Second, at the acceptance threshold $p^1 = p_S^1(s, b)$ the seller is (weakly) willing to accept. With $U_S(s) > 0$, this requires $\Big((1-t)p_S^1(s, b) - s\Big) \geq 0$, hence $U_S(s) - (1-t)p_S^1(s, b) + s \geq 0$. Therefore $H_b\Big(b, p_S^1(s, b)\Big) \geq 0$, and it is strictly positive whenever $f_S\Big(s^*(b, p_S^1)\Big) > 0$ and $\partial s^* / \partial b > 0$. It follows that $\partial p_S^1 / \partial b(s, b) < 0$. □

A.2 Hedonic regression results

This appendix reports the hedonic regression used to residualize list prices and offers. The specification controls for observable item characteristics and shipping attributes. The fitted values are used to construct residualized prices and offers that enter the main analysis.

Table 8: Hedonic price regression

	List price (1)
Constant	14584.538 (454.439)
Condition: Some scratches	-1540.795 (71.508)
Condition: Scratched	-3437.442 (87.886)
Shipping payer: Seller pays shipping	-1665.865 (548.765)
Shipping duration: Ships in 2–3 days	-127.359 (75.329)
Shipping duration: Ships in 4–7 days	-156.073 (132.291)
Observations	13391
R^2	0.117
Adjusted R^2	0.113
Residual Std. Error	3663.424 (df=13324)
F Statistic	26.786 (df=66; 13324)

Notes: The specification includes prefecture fixed effects and shipping-method fixed effects. The intercept corresponds to the reference categories for all covariates (no visible scratches, buyer paid shipping, shipping within 1–2 days, the platform default shipping option, and the baseline prefecture).

A.3 Estimation Details

Recovering unconditional choice probabilities. I denote $\tilde{\lambda}_S(s)$ as the arrival rate of an observable match to seller s. I estimate $\tilde{\lambda}_S(s)$ based on the days T^{obs} between consecutive observed arrivals for a given listing. Then $\tilde{\lambda}_S(s)$ is identified:

$$\tilde{\lambda}_S(s) = \frac{1}{\mathbb{E}[T^{obs}|s]}$$

To avoid numerical instability due to inversion, I first estimate $\mathbb{E}[\log T^{\text{obs}} \mid s]$ after dropping very short intervals (less than ten minutes), and apply Duan's smearing correction to recover an estimate of $\mathbb{E}[T^{\text{obs}} \mid s]$. I then define $q(s)$ as the probability a match is observed. Then we have:

$$\tilde{\lambda}_S(s) = q(s)\lambda_S$$

I recover $q(s)$ from this relationship.

I denote $p_\chi(s) = \mathbb{P}(\chi_B(s,b) = \chi \mid s)$ for $\chi \in \{A, CN, CS, D\}$. Let $\tilde{p}_\chi(s)$ be the probability that action χ is taken conditional on an observable match. Then, because $\chi \in \{A, CN, CS\}$ is always observable,

$$p_\chi(s) = q(s)\tilde{p}_\chi(s), \qquad \chi \in \{A, CN, CS\}.$$

Finally, the unconditional decline probability is obtained as the residual

$$p_D(s) = 1 - p_A(s) - p_{CN}(s) - p_{CS}(s).$$

Online Appendix (Not for Print)

B Dataset Construction

B.1 Selection of Subsample

Mercari provided data covering over 400 million items listed during the year from 2019 to 2021. I first restrict attention to items listed in the "Smartphones" category within "Mobile Phones," which is nested under "Home Appliances, Smartphones, and Cameras." This yields 763,079 items.

I then restrict the sample to iPhones. Items are classified as iPhones if either the brand name is recorded as Apple or, because the brand field is frequently missing, the item title or description contains the string "iPhone," allowing for common orthographic variants. This restriction leaves 414,363 items.

Next, I infer the iPhone model from the item title or description text. iPhone 7 is the most frequently traded model in the data, resulting in a subsample of 61,132 items. I similarly infer storage capacity from the title or description. Among iPhone 7 listings, 128GB is the most common storage size, with 32,030 items.

I then examine the distribution of list prices by item condition within the iPhone 7 128GB subsample. As shown in Figure 4, the price distributions for conditions “No noticeable damage”, “Some damage”, and “Damaged” are similar to each other and clearly distinct from the remaining conditions. I therefore restrict attention to items in these three item conditions for the main analysis, leaving me with 28,230 items.

I further restrict the sample to items listed on or after June 24, 2020, when price change records begin to be consistently available, leaving 13,397 items.

B.2 Cleansing of the Dataset

I extract offer amounts from comments as follows. For each comment, I first normalize numeric expressions and parse them into numbers. I then retain values between 5,000 and 30,000 and exclude any values that coincide with previously observed list prices, price changes,

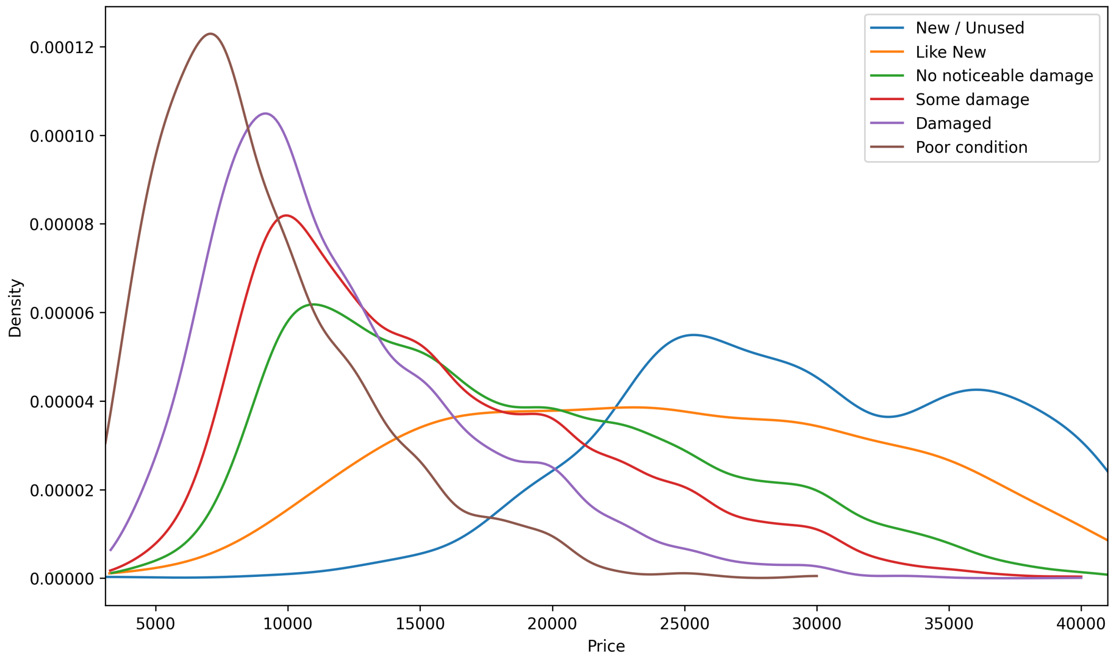

Figure 4: Distribution of prices by item condition

Notes: The figure plots kernel density estimates of listing prices for the iPhone 7 128GB subsample, separately by the platform reported item condition. For visual clarity, prices are trimmed to the 1st and 99th percentiles of the price distribution within this subsample prior to density estimation.

or earlier offers for the same item. If multiple candidates remain, I select one as the offer amount.

The seller can change its list price even without receiving an offer from a buyer. I therefore treat the price after any price changes that occurred before any offer from a buyer as the effective list price. I define a match as the first arrival of a distinct buyer, identified by a non-seller comment or purchase. An item is flagged as having multiple-match buyers if a buyer reappears after another buyer has arrived.

I label seller and buyer actions at the match level as follows. An offer is classified as accepted if the seller subsequently updates the posted price to exactly the offer amount after the offer is made. Using this information, each buyer–item match is assigned an action type: C if the match includes an accepted offer, A if the item is sold without any offer from that buyer, and D otherwise. For matches of type C, I further classify buyer behavior by defining a walkaway indicator equal to one if the offering buyer does not complete the purchase. Finally, I label buyer commitment by setting a commit indicator equal to one if any comment

Table 9: Commitment-related expressions

Japanese	English meaning	Count
sokketsu	Immediate decision / buy outright	625
soku kounyuu	Buy immediately	520
sugu	Immediately / right away	353
shiharai	Payment	147
oshiharai	Payment	60
hayame	Early / sooner	49
honjitsu chuu	By today	42
nyuukin	Payment made / remittance	39
hayaku	Quickly	32
kyou chuu	Within today	20
sugu ni	Right away	19
isogi	Urgent	17
gozen chuu	By the morning	15
sokujitsu	Same day	13
kanarazu	Definitely / for sure	13
isoide	In a hurry	7
ashita chuu	By tomorrow	7
kettei	Decision	6
saitan	As soon as possible	5
kimeru	Decide	2

Notes: The table reports the number of accepted-offer matches (action model C) in which each expression appears in the negotiation comments. The unit of observation is an observable match, defined as the arrival of a distinct buyer through a non seller comment or a purchase. Each expression is counted at most once per match, regardless of how many times it appears within the same negotiation.

within a C-type match contains keywords indicating an intention to complete the transaction promptly. The list of keywords are shown in Table 9.

The analysis starts from a sample of 13,397 items. I first drop 6 items with missing residualized list prices, leaving 13,391 items. I then exclude 204 items for which either the residualized offer amount or the residualized sales price exceeds the residualized list price, reducing the sample to 13,187 items. Finally, I trim 736 items that fall outside the 1st - 99th percentile range of the residualized list price and the time to first match, yielding a final analysis sample of 12,451 items. In total, 946 items are removed across all trimming steps.

C Simulation of the Equilibrium

I compute the stationary equilibrium by value function iteration on discretized state spaces, taking the estimated primitives and calibrated parameters as given.

Discretization. I use 100 grid points each for seller values s and buyer values b, constructed by drawing from the estimated distributions and sorting the draws. I discretize feasible prices on a uniform grid with 200 points over $[0, 100000]$. I fix $(t, r, c, \lambda_S, \lambda_B, \lambda_R, \kappa)$ and (N_S, N_B) at their estimated or calibrated values. In the full commitment counterfactual, I set $c = \infty$ and hold all other primitives fixed. I initialize $U_S(s)$, $U_B(b)$, and $V_B(s, b)$.

Policy updates given (U_S, U_B, V_B). For each iteration, I update the equilibrium policies implied by the current value functions.

First, I compute the committed acceptance price $p_N^1(s)$ from (4). Second, I compute the noncommitted acceptance price $p_S^1(s, b)$ by searching over the discretized price grid for the smallest p^1 that satisfies the seller acceptance condition (2). This step uses the walkaway cutoff $s^*(b, p^1)$ defined by $V_B(s^*, b) = p^1$ and the induced walkaway probability $F_S(s^*(b, p^1))$.

Given $\{p_N^1, p_S^1\}$, for each candidate list price p^0 I evaluate buyer continuation values for $\chi \in \{A, CN, CS, D\}$ using the payoff expressions in (5) and choose the maximizing action $\chi_B(s, b; p^0)$. Finally, I compute the seller optimal list price $p^0(s)$ by maximizing the objective in (8), integrating over the 100 point buyer grid and the induced buyer actions.

Value updates, stabilization, and convergence. Using the updated policies, I update U_S, U_B, and V_B using their definitions in Section 4. For numerical stability, I smooth the updated value functions at each iteration using a Gaussian kernel with bandwidth 5 on the discretized state grids. I iterate until the relative change in both U_S and U_B falls below 10^{-3}.