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The Effects of Delay in Bargaining: Evidence from eBay

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Abstract. Delay in negotiations is common in many settings, but the effects of delay have rarely been studied empirically in the field. We measure the causal effects of delay on bargaining outcomes using data from millions of negotiations on eBay. We find that for both buyers and sellers, the longer the bargaining party delays, the less likely the opponent is to continue the negotiation by countering, and the fewer rounds the negotiation takes to complete. The effects of delay are robust; they exist even under short amounts of delay (under six hours) and for negotiations for low-priced goods. We find that these effects are consistent with models of strategic delay, in which delay acts as a signal of bargaining power.

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Keywords: bargaining • negotiations • e-commerce • digital platforms

1. Introduction

Bargaining is one of the oldest and most common methods by which parties trade goods and services. It motivated a significant body of theoretical literature that examines how parties bargain in different environments and a large experimental literature that investigates how negotiations unfold through laboratory experiments. Historically, however, empirical studies that utilize field data have been relatively rare because of limited data availability, particularly data that include unsuccessful negotiations and the evolution of negotiations (e.g., information about offers other than the final one). Although richer field data that contain such information are now more readily available, several key features of bargaining are yet to be studied in the field.

One such feature is delay. Apart from the monetary offers themselves, delay is often one of the few levers that parties can use in negotiations. Thus, it is unsurprising that delay in bargaining has been documented across a wide array of settings, such as strikes (Kennan and Wilson 1989), legal disputes in the stock market (Mnookin and Wilson 1989), ransom negotiations (Hurlburt 2013), trade agreements (Hoffman 1950), and medical malpractice claims (Danzon and Lillard 1983). In addition, advice on negotiation strategies often emphasizes the importance of timing (Hughes and Ertel 2020). However, despite the prevalence of delay in bargaining, the understanding of how, why, and under what conditions delay can impact bargaining outcomes is still limited.

This paper takes a step toward filling this gap by empirically examining delay in bilateral bargaining using large-scale field data. In particular, we use publicly available data from Backus et al. (2020), which contain tens of millions of negotiations for goods conducted between buyers and sellers on eBay's Best Offer platform, to investigate whether and how delay impacts bargaining proceedings and outcomes. We focus on how the seller (buyer) delay impacts the buyer's (seller's) propensity to accept, decline, and counter an offer; the probability that the negotiation is successful; and if so, the transaction price.

We identify the causal effects of delay using an instrumental variables approach. Importantly, we refer to "causal effect" throughout as the endogenous relationships between delay and outcomes rather than as an economic primitive. In our empirical application, we define delay as the amount of time between a party's offer and their opponent's response.[1] On average, buyers delay their counteroffers by 6.1 hours, whereas sellers delay their counteroffers by 5.4 hours.

Because an offer on eBay is valid for 48 hours, these quantities correspond to 12.7% and 11.25% of the validity time of the offer, respectively. We find that delay has significant and robust effects on buyer and seller behavior. Delay reduces the likelihood that the other party continues to negotiate and thus, reduces the length (i.e., number of total offers) of the negotiation. Doubling the average seller delay decreases the probabilities of buyer acceptance and countering by 2.3% (0.4 percentage points) and 6.3% (1.7 percentage points), respectively, and increases the probability of buyer rejection by 3% (1.9 percentage points). In other words, seller delay causes buyers to substitute from countering to declining. In turn, buyer delay causes sellers to substitute from countering to accepting; doubling buyer delay increases the probability of the seller acceptance by 5% (1.3 percentage points), decreases the probability of seller countering by 4.4% (2.1 percentage points), and increases the probability of the seller declining by 3% (0.86 percentage points).

Furthermore, seller delay also has meaningful and statistically significant impacts on negotiation outcomes. Doubling seller delay decreases the probability that the product is sold by 4.4% (1.3 percentage points). Doubling seller delay also increases the final price relative to the buyer's initial offer, although the effect is small in magnitude ($0.74 increase). We find no such effects from buyer delay.

These effects of delay on the other party's response exist even in circumstances under which one would expect delay not to be important, such as in relatively short periods of delay (less than average) and in lower-stakes negotiations (goods with low buy it now (BIN) prices). Doubling the delay for goods with BIN prices below $30 reduces the buyer and the seller counters by 9% and 7%, respectively.[2]

Measuring the causal effects of delay outside the laboratory is challenging for several reasons. Traditionally, the main challenge has been the lack of data that contained information about the timing of offers. This is one of the reasons that the employed data set from eBay is suitable for this exercise; it contains such information for tens of millions of bargaining interactions in addition to rich information about goods, sellers, buyers, and market conditions. However, observing the timing of offers is not sufficient to obtain causal estimates because delay can be endogenous to the bargaining parties' attributes, even after controlling for the many covariates that we observe.

To overcome this endogeneity challenge, we need variation in the time that a buyer or a seller takes to make a counteroffer that is not correlated with the attributes of the item under negotiation or the opposing party. We obtain this variation by leveraging the fact that we observe many instances in which the same party is involved in different negotiations over time. We assume that a bargaining party's decision about how much to delay depends not only on the attributes of the product under negotiation and the opponent but also, on unrelated shocks, like time spent on the internet. These shocks are correlated across this party's negotiations over time (i.e., a person might be more likely to spend more time on the internet today if that person spent more time on the internet recently). This assumption allows us to employ this person's decisions (e.g., delay) from a previous negotiation with a different opponent for a different item as instrumental variables for the decisions during the focal negotiation in a way similar to the instruments introduced in Hausman (1997). This identification (ID) strategy is only possible because of the popularity of eBay and the comprehensiveness of this data set, which is another reason that this setting and these data are especially suited to this exercise.

We then proceed to investigate some potential mechanisms behind our empirical findings. In this analysis, we use Cramton (1992) as a reference point. Cramton (1992) considered a bargaining game under two-sided incomplete information, similar to a war of attrition. Akin to one of Cramton's results, we find that the empirical effects are consistent with delay signaling the bargainer's valuations. Under this setup, bargainers who stand to gain more from trade, as measured by the difference between the buyer's and the seller's valuations of the product, are more impatient because of time discounting and as a result, delay less. Consequently, in equilibrium, with all else constant, long seller delays lead the buyer to infer that the seller's valuation is high, making the buyer less likely to continue the negotiation (i.e., counter). Analogously, the same is true for buyer delay; buyers who delay more have low valuations, which the seller correctly infers, thereby decreasing the likelihood that the seller will continue the negotiation. Hence, the theoretical prediction would be that seller (buyer) valuations should be positively (negatively) correlated with delay. Using offer prices relative to the prices of similar goods as a proxy for valuations, we find this prediction to be true.

We also present potential explanations for the asymmetric result on acceptances and refusals, which are that in response to delay, sellers are more likely to switch from countering to accepting, whereas buyers are more likely to switch from countering to declining. One possible explanation is that on eBay, buyers have greater bargaining power than sellers. This bargaining power can arise from different levels of impatience (i.e., buyers are more patient than sellers), buyers having lower valuations than sellers, or buyers having better outside options than sellers. Consequently, a buyer prefers to decline rather than spend effort coming to an agreement, whereas a seller would rather concede than find another buyer. This explanation is consistent with two empirical patterns. (1) On average, sellers are more likely to accept than decline, whereas buyers are more likely to decline than accept. (2) The effect of the concession weight on whether the other party counters is opposite for buyers and sellers; sellers are *less* likely to counter if the buyer concedes more, whereas buyers are *more* likely to counter if the seller concedes more. Another reason that buyers may choose to decline rather than negotiate further when sellers delay is that the longer a seller delays the response, the higher the likelihood that the buyer will lose interest in the seller's product. This explanation is connected to the previous one; when buyers hold more bargaining power, they are more prone to losing interest and consequently, declining the offer when faced with delays.

It is essential to note that we cannot test or reject whether bargaining parties are indeed strategic in their delay; we can only assess whether the data are consistent with these strategies. Although the effects of delay are consistent with the predictions from Cramton (1992), in which delay can be seen as acting as a signal of the bargainer's valuation because of time discounting, we cannot isolate whether empirically, in our setting, delay is indeed driven by time discounting. That is, we cannot determine whether delay signals the bargainer's valuation of the product or other factors that influence bargaining power, such as the level of impatience. For example, more patient buyers may delay more, and sellers may infer that more patient buyers are less likely to compromise.

Our analysis has other limitations. Despite its richness, the data set that we use lacks important information. It does not provide the identity of the product (e.g., an iPhone or a Samsung Galaxy). Hence, we are unable to focus on specific products to perform more detailed and potentially more interpretable analyses. Furthermore, the data tell us whether buyers and sellers exchanged messages but not their content. This constraint prevents us from assessing the effects of communication and how they relate to delay.

The paper proceeds as follows. In Section 2, we present the related literature on delay in bargaining. Section 3 describes the setting and the data, and Section 4 presents our empirical strategy and descriptive evidence of delay in negotiations. Section 5 presents our main results and several robustness checks, and Section 6 describes the potential mechanisms behind them. We conclude in Section 7.

2. Related Literature

The literature on bargaining is vast, and it is not our objective to provide a full summary. Thus, we focus on the subset of this literature that is closely related to this study, especially focusing on delay in bargaining.

2.1. Microeconomic Theory

Our main objective is to assess whether delay can impact bargaining outcomes using field data. Delay in bargaining has received considerable attention in microeconomic theory. Here, we briefly summarize this work.

This vast literature was perhaps in part motivated by the well-known and surprising "no delay" result first obtained by Rubinstein (1982); in a negotiation with alternating offers between a buyer and a seller, in equilibrium, an agreement is reached immediately after the first offer without delay. Rubinstein (1982) considered a model with complete information in which the buyer and the seller know each other's discount rates and have to "split a pie" of size 1. Because delay often arises in practice, several studies have since proposed models that depart from this setting in attempt to find equilibria with delay. Nevertheless, even though several papers proposed models capable of generating delay in equilibrium, the "no delay" result is surprisingly robust.[3]

It is not our main intention to detect and explain the specific mechanisms through which delay can impact bargaining outcomes, which may vary across different models that can generate delay in equilibrium. That said, one feature that is worth highlighting is the nature of incomplete information. In our setting, the source of incomplete information is arguably two sided; the seller does not know how much the buyer values the product and vice versa. Nevertheless, most papers that were able to generate delay in equilibrium considered models with one-sided incomplete information.[4]

Of all papers that were able to generate delay in equilibrium, perhaps the one whose model resembles our setting the most is that of Cramton (1992). This is because Cramton's model features two-sided incomplete information and alternating offers while allowing the players to endogenously time their actions.[5] However, it is important to note that the main contribution of Cramton (1992) is in addressing general war of attrition games under two-sided incomplete information, of which bargaining can be seen as just one example.[6]

2.2. Results from the Field

Empirical studies using field data have long been limited by the absence of data sets that consisted of offer-level observations and included unsuccessful negotiations. These limitations have been overcome relatively recently, and we now discuss studies that, like our study, address delay in bargaining using field data.

The importance of delay in bargaining has long been recognized, for example, by studies that addressed strikes and negotiations between unions and employers as surveyed by Kennan and Wilson (1993). More recently, the potential key role of delay in bargaining has been considered by Goetz (2019) in the context of mergers.

More directly related to our paper are several recent studies that have used the publicly available data set provided by Backus et al. (2020), which has the advantage of containing offer-level observations for successful and unsuccessful negotiations on eBay's Best Offer platform.[7] However, few papers have used these data to study delay in bargaining specifically. Green and Plunkett (2022) use them to estimate a deep reinforcement learning model that trains agents to bargain optimally. Although their model does not allow the agent to choose when to make an offer, the opponent's delay is an input of the model. Therefore, delay—and how it correlates with offer amounts and expectations about future offers—impacts bargaining strategies. Cotet and Krajbich (2025) use the Best Offer data to study the relationships between offer sizes and response times; however, their analysis is entirely descriptive and ignores matters of endogeneity. Because our objective is to recover credible estimates of the causal effects of delay bargaining outcomes, we address endogeneity concerns using an instrumental variables approach. Send and Serena (2022) used the eBay data to study insistence in bargaining, in which the seller demands the same asking price more than once.

To our knowledge, the only other study that estimated the causal effects of delay on bargaining outcomes from field data is Ambrus et al. (2018), who use data on thousands of captives ransomed in Algiers by Barbary pirates between 1575 and 1692. In particular, their focus was on estimating the effect of delay on the final negotiated price. To recover this effect, they used as instruments of delay the distance between the captives' respective hometowns (where their family and friends lived), the cities where the bargaining teams were based, and the ports commonly used to sail to Algiers. Similarly to Ambrus et al. (2018), we also employ an instrumental variables strategy to recover the causal effects of delay. Nevertheless, there are three differences worth noting between Ambrus et al. (2018) and our study.

The first difference concerns the estimands of interest and is partially a consequence of the differences between the data that we use and those from Ambrus et al. (2018). The richness of the eBay data enables us to investigate the effects of delay on several quantities: the probabilities that the opposing party counters, accepts, or declines an offer; the probability that the negotiation is successful; and the final split of gains between buyers and sellers when negotiations are successful. In turn, the main focus of Ambrus et al. (2018) is solely on estimating the effect of delay on the final negotiated price, which in accordance with what several models predict, is negative. This is in part because of data limitations as their data set does not contain offer-level information and consists only of successful negotiations. Consequently, our analysis can provide a more complete picture of how delay impacts bargaining outcomes, especially because unlike Ambrus et al. (2018), we can assess how it affects a negotiation's success or failure.

The second difference relates to our end goals vis-à-vis those of Ambrus et al. (2018). Our exercise consists solely of obtaining credible estimates of the causal effects of delay on bargaining outcomes. On the other hand, Ambrus et al. (2018) take a step further and also estimate a structural model of bargaining that enables them to perform counterfactual exercises, where they assess the consequences of the use of different bargaining protocols, such as bundling. We chose not to attempt to perform this type of exercise because as noted by Freyberger and Larsen (2025), a theoretical characterization of equilibria of the bargaining game played on eBay does not exist, which renders the identification of the primitives of a bargaining model challenging.

The third difference, which is conceptual and more minor, arises solely from the different settings under consideration. Ambrus et al. (2018) argue that their setting is one in which one-sided incomplete information is a reasonable assumption. Thus, they guide their analysis through a model that maintains this assumption and where only one party makes offers à la Fudenberg et al. (1985). In turn, following the extant literature, such as Freyberger and Larsen (2025) and Keniston et al. (2024), we treat the eBay environment that we study as one in which incomplete information is two sided. This is partly what makes the estimation of a complete structural model challenging.

2.3. Results from the Laboratory

Many studies have used laboratory experiments to test theories of bargaining dating back at least to Roth (1985). Here, we will focus on studies that specifically address delay.

Theoretical predictions and the role of time preferences have received considerable attention with somewhat contradictory results. Srivastava et al. (2000) tested the predictions from the sequential equilibrium obtained by Grossman and Perry (1986) under alternating offers, one-sided incomplete information, and discounting. They found that the direction of the effects hold but not their magnitude; in particular, they found that delay is longer than predicted by the authors.

In turn, Srivastava (2001) focused on what players infer from delay, rejecting the signaling mechanism from Admati and Perry (1987) and Cramton (1992). Van de Calseyde et al. (2014) found that agents can infer the degree of uncertainty that their opposing party faces, whereas Desai and Jindal (2024) assessed how delay by a party can inform their opponent of their own valuation in a setting where delay is unanticipated and noninferential. The signaling mechanism relies on time discounting and its implications for the costs from delay. One potential explanation for this finding is that time preferences simply do not change behavior as found by Manzini (2001).[8] Nevertheless, Kim et al. (2024) obtained the opposite result: that is, that discounting does affect behavior under a complete information setup.

Other studies considered the differences between strategic and nonstrategic uses of delay. For instance, Ghosh (1996) considered the effects of nonstrategic delay between offers and counteroffers in a finite-horizon, alternating-offer bargaining game with incomplete information but no discounting, focusing on specific mechanisms rather than negotiation outcomes. Chen et al. (2023) compared the use of delay when a party was aware versus unaware that the opposing party would observe delay and found evidence of its strategic use. Konovalov and Krajbich (2023) further outline and test conditions under which agents use delay strategically. More specifically, they found that speeds of acceptances and rejections are informative of valuations, but they did not study the speed of counteroffers.

Overall, similar to theoretical work, experimental findings seem to be specific to the particular designs used. Therefore, it is not surprising that some of the results that they obtain are in opposition to one another and to our own findings. As such, it is not clear how the effects would generalize to bargaining behavior in e-commerce platforms, the setting of our study.

3. Data

The context of this paper is bargaining on eBay, a large e-commerce platform founded in 1995. Although traditionally known for auctions, in 2005, eBay launched its "Best Offer" feature, which allows for bargaining between buyers and sellers. More specifically, the feature allows buyers to make offers for sellers' listings. The seller can respond by accepting, declining, or making a counteroffer. The buyer can then respond to the seller's counteroffer by accepting, declining, or countering; this process iterates until an offer is accepted or a party declines. Each bargaining party can make up to three offers, and each offer expires after 48 hours.[9]

We use bargaining data from the Best Offer feature, provided by Backus et al. (2020), which consist of offers and counteroffers for listings on eBay from May 31, 2012 until June 1, 2013. Like Backus et al. (2020), we define a negotiation or bargaining thread as a unique combination of a buyer-seller-product. Each negotiation has at least two rounds. We define rounds as follows. In round 0, the seller creates the listing, and in round 1, the buyer makes an offer. In round 2, the seller responds to the buyer's offer by accepting, countering, or declining; if the seller counters, the buyer responds to the seller's counteroffer in round 3. Table 1 provides a timeline under our notation and the sequence in which buyers and sellers make offers.

Because our focus is on the effects of delay, which occurs only for counteroffers, our data comprise the first counteroffer from each party and the opponent's response to the counteroffer. To provide a sense of how often sellers and buyers counteroffer, a seller counters a buyer's first offer 28% of the time, and a buyer counters the seller's first counteroffer 25% of the time conditional on the seller countering.[10] In addition, we only select counteroffers that are a response to the opponent's offer.[11] Thus, our sample contains only threads in which the seller has at least one counteroffer. This subset of threads is for listings that tend to have higher BIN prices and lower first offers from buyers (relative to the BIN price) compared with all listings. Table D.1 in the Online Appendix provides summary statistics of listings in the entire data set compared with our subset of listings.

For each offer, we observe the time that the offer was sent and its amount. We also observe whether the bargaining party sent a message with the offer (but not the message's content); the listing's characteristics (item condition, product category, number of photos, and BIN price); buyer characteristics (number of prior threads that the buyer participated in); and seller characteristics (rating and number of prior threads that the seller participated in).[12] Following Backus et al. (2020), we denote the concession weight in round r of thread k as γ_{kr}, where $p_{kr} = \gamma_{kr} p_{k,r-1} + (1-\gamma_{kr}) p_{k,r-2}$ for $r \geq 2$. In words, γ_{kr} quantifies how much weight the player

Table 1. Timeline of a Bargaining Thread k

Round	Buyer and seller actions
$r = 0$	Seller lists the item and chooses BIN price p_{k0}.
$r = 1$	Buyer makes initial offer p_{k1}.
$r = 2$	Seller responds with y_{k2}. If $y_{k2} = C$, seller makes counteroffer p_{k2}.
$r = 3$	Buyer responds with y_{k3}. If $y_{k3} = C$, buyer makes counteroffer p_{k3}.
$r = 4$	Seller responds with y_{k4}. If $y_{k4} = C$, seller makes counteroffer p_{k4}.

Notes. This table describes the sequence of offers and the notation for rounds 0–4. The possible outcomes for each offer, y_{kr}, are accept (A), counteroffer (C), and decline (D).

Table 2. Offer Descriptive Statistics

Variable	Mean	Standard deviation	Min	Median	Max
Seller counteroffers					
Concession Weight (γ)	0.43	0.21	0.00	0.42	1.00
Response Time (hours)	5.45	8.50	0.00	1.59	48.00
Other Party Accepts	0.16	0.37	0.00	0.00	1.00
Other Party Declines	0.55	0.50	0.00	1.00	1.00
Other Party Counters	0.25	0.44	0.00	0.00	1.00
Buyer counteroffers					
Concession Weight (γ)	0.38	0.20	0.00	0.38	1.00
Response Time (hours)	6.62	10.27	0.00	1.46	48.00
Other Party Accepts	0.30	0.46	0.00	0.00	1.00
Other Party Declines	0.22	0.42	0.00	0.00	1.00
Other Party Counters	0.46	0.50	0.00	0.00	1.00

Notes. This table displays descriptive statistics for counteroffers from buyers and sellers. The numbers of observations for sellers and buyers are 7,508,001 and 1,898,299, respectively.

making the offer at t places on previous offers. If $\gamma_{kr} = 0.5$, then the player making the offer "splits the difference." We remove offers for listings in the top 1% of BIN prices and offers where the concession weights are not in $[0, 1]$. Online Appendix A provides a detailed explanation of how the data set is constructed. This leaves us with the final data: sellers' first counteroffers and the corresponding buyers' responses, which consist of 7,508,001 offers for 5,916,590 listings from 546,925 sellers, and buyers' first counteroffers and the corresponding sellers' responses, which consist of 1,898,299 offers for 1,770,887 listings from 303,740 buyers.

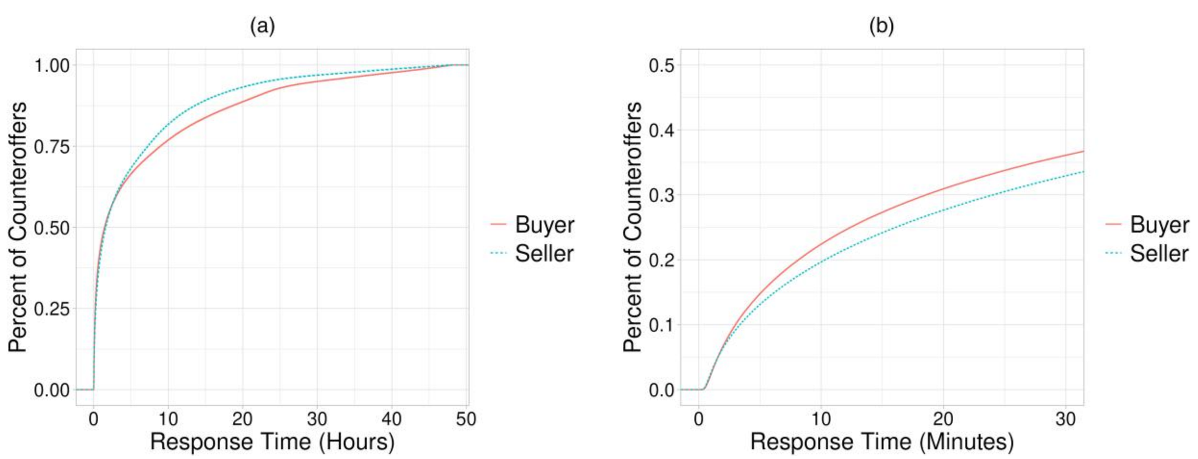
We provide descriptive statistics for these counteroffers in Table 2.[13] We code offers that expire as declined offers.[14] Conditional on the seller making a counteroffer, the buyer accepts 16% of the time, counters 25% of the time, and declines 55% of the time.[15] Conditional on the buyer making a counteroffer, the seller accepts 31% of the time, counters 46% of the time, and declines 22% of the time.

Both parties counter quickly. Conditional on countering, the median time that it takes for a buyer to respond to the opponent's offer is 1.59 hours, and the median time that it takes for a seller to respond to the opponent's offer is 1.48 hours.[16] Figure 1(a) plots the empirical cumulative distribution function (CDF) of the response time in hours. Although most buyers and sellers respond within 12 hours of the previous offer—85% of sellers and 80% of buyers—many respond much sooner. Figure 1(b), which plots the empirical CDF for the first 30 minutes, shows that approximately 20% of counteroffers are made within 10 minutes of the opposing party's offer. In fact, 2.6% of seller counteroffers are made within the first minute of the buyer's initial offer. Similarly, for buyer counteroffers, 2.4% are made within the first minute of the seller's initial counteroffer.

4. Empirical Strategy

We now present our empirical strategy to measure the causal effects of delay on negotiation outcomes. First,

Figure 1. (Color online) Empirical Cumulative Distribution Function (CDF) of Response Times



Notes. This figure plots the empirical CDF of the response times for buyer and seller counteroffers. Panel (a) plots the CDF for the entire data set, where the maximum response time is 48 hours. Panel (b) zooms in on the first 30 minutes.

we describe the relationship between delay and the other party's response without accounting for the endogeneity of delay. Second, we describe the endogeneity challenge that we face. Finally, we present our identification strategy in detail.

4.1. Relationship Between Delay and the Opponent's Response

To estimate the relationship between delay and the opponent's response, we estimate the following logistic regression:

$$y_{k,r+1} = \sum_{d=0}^{D} \beta_r^d \mathbb{1}\{w_{kr} \in I_d\} + \beta_r^{\gamma}\gamma_{kr} + \boldsymbol{x}_k'\boldsymbol{\beta}_r^x + \epsilon_{k,r+1}, \quad (1)$$

where k denotes a thread and r denotes the round. We consider several outcomes of interest $y_{k,r+1}$, such as indicators of whether the other party accepted, countered, or rejected the offer; an indicator of whether the negotiation was successful; and the transaction price conditional on sale. We denote delay by w. Recall that w_{k2} is the amount that the seller delays and w_{k3} is the amount that the buyer delays. To take a more flexible approach, we divide w_r into ranges. The variable I_d denotes an interval of time (e.g., 0–1 minute, 1–10 minutes, etc.). The variable γ denotes the concession weight. We follow the empirical literature by standardizing offer amounts (such as Backus et al. 2020, Larsen et al. 2024, and Freyberger and Larsen 2025) and use the concession weight instead of the dollar amount. Our coefficients of interest are β_2^d for $d \in \{0, \ldots, D\}$, which capture the effect of seller delay in round 2 on outcomes in round 3, and β_3^d for $d \in \{0, \ldots, D\}$, which capture the effects of buyer delay in round 3 on outcomes in round 4. Note that the dependent variables—the indicators of whether the opposing party accepts, rejects, or counters—are interconnected (e.g., if delay increases accept and reject rates, it must decrease counter rates by definition). Hence, the sum of the estimated effects from the three regressions should be approximately zero.

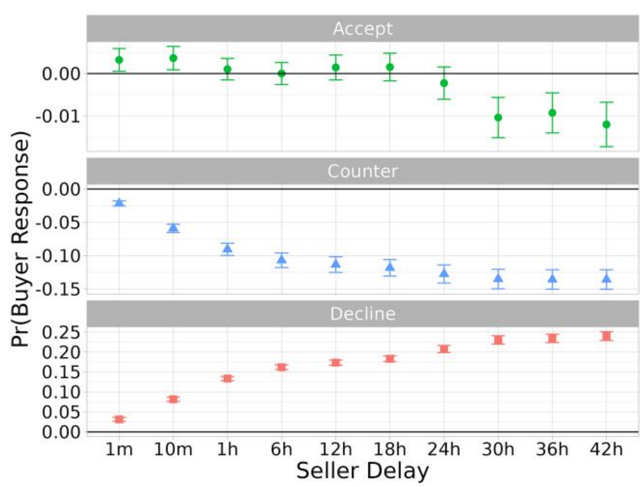
Equation (1) also includes various other covariates of the buyer, the seller, and the product, denoted by the vector $\boldsymbol{x}$, that can affect negotiation outcomes. This vector includes buyer and seller fixed effects to account for potential types that do not vary over time. For example, certain people might be inherently busy and thus, have less time to negotiate. Moreover, we include the seller's rating (as measured by the logged number of ratings that the seller has received, which the buyer observes) and bargaining experience of the seller and the buyer, which is measured by the logged number of negotiations in which they were involved in the past. In addition, we include an indicator of whether the buyer and the seller exchanged a message to capture any interactions between them besides direct offers.

To account for characteristics of the product, we include category fixed effects, the number of product photos, and indicators of item condition (new, used, and so on). In addition, we add an indicator of whether the BIN price was a round number because this can be a relevant and informative signal (Backus et al. 2019).

Finally, we add year-month and day-of-the-week fixed effects. The former accounts for market conditions that can potentially affect how the parties bargain. For example, valuations of the product might be higher during holidays. Day-of-the-week fixed effects account for the parties' available time to negotiate. For example, buyers and sellers may have more time on weekends, which potentially affects delay.

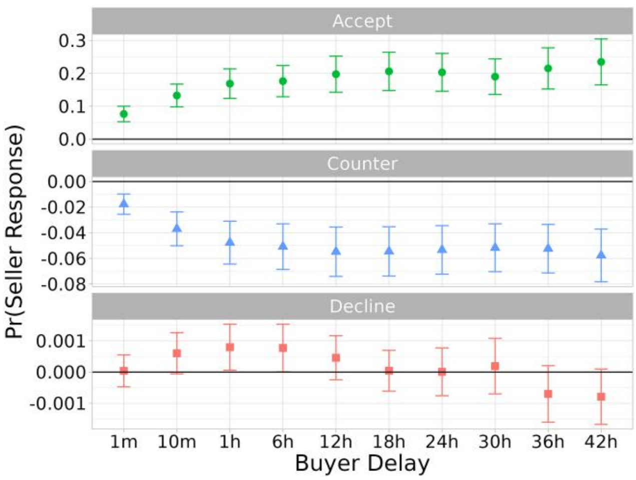
For ease of interpretation, we report the average marginal effects of seller and buyer delay on the opposing party's responses in Figures 2 and 3, respectively.[17] The displayed average marginal effects are relative to an omitted category where the seller or buyer delay is less than one minute. Figure 2 shows a strong correlation between delay, countering, and declining; a buyer is 13 percentage points less likely to counter and 20 percentage points more likely to decline if the seller takes 24 hours to respond to the buyer's first offer than if the seller takes less than one minute to respond. The correlation between seller delay and buyer acceptance is relatively less clear; relative to responding in the first minute, the buyer is more likely to accept if the seller responds within the first 24 hours, but this effect becomes indistinguishable from zero for delays

Figure 2. (Color online) Estimates of Equation (1): Average Marginal Effects of Seller Delay on Buyer Response



Notes. This figure plots the average marginal effects of seller delay on whether the buyer accepts, counters, or declines. Each effect is relative to a seller delay of zero to one minute (e.g., the seller responds to the buyer's first offer within one minute). Error bars represent 95% confidence intervals derived from standard errors clustered at the seller level (546,925 sellers). The coefficient estimates are reported in Table D.3 in the Online Appendix.

Figure 3. (Color online) Estimates of Equation (1): Average Marginal Effects of Buyer Delay on Seller Response



Notes. This figure is analogous to Figure 2 but for buyers. The x variable is buyer delay, and the dependent variables are the probabilities for whether the seller accepts, counters, or declines. Error bars represent 95% confidence intervals derived from standard errors clustered at the buyer level (303,740 buyers). The coefficient estimates are reported in Table D.4 in the Online Appendix.

between 1 and 24 hours and negative for delays longer than 24 hours.

We find a similar effect of buyer delay on the probability that the seller counters, which is shown in Figure 3. A 24-hour delay in the buyer's counteroffer is associated with a five-percentage-point reduction in the probability that the seller counters relative to if the buyer had countered within the first minute of the seller's previous offer. In addition, we find that longer buyer delays are associated with higher probabilities that the seller accepts and are not associated with any changes in the probability that the seller declines.

Although we find strong correlations, these results ignore the potential endogeneity of delay. In the following sections, we describe the sources of this endogeneity and how we address this issue.

4.2. Data-Generating Process

To discuss why delay and concession weights can be endogenous, we first explicitly outline the data-generating process (DGP). Our objective is not to propose an explicit model of equilibrium behavior. Instead, we simply assert a descriptive behavioral model to illustrate the sources of endogeneity.

Consider the buyer's first offer for an item in a negotiation k. The first offer amount and delay, respectively, for the item are

$$p_{k1} = f^{p}_{k1}(p_{k0}, \boldsymbol{x}_k, B_k, \tilde{S}_k, \eta^{p}_{k1})$$
$$w_{k1} = f^{w}_{k1}(p_{k0}, \boldsymbol{x}_k, B_k, \tilde{S}_k, \eta^{w}_{k1}), \qquad (2)$$

where $\boldsymbol{x}_k$ is a vector with the item's attributes that are observed by the two parties and the econometrician; B_k is the buyer's residual valuation after taking $\boldsymbol{x}_k$ into account; $\tilde{S}_k$ is the buyer's expectation of the seller's residual valuation; and η^{p}_{k1} and η^{w}_{k1} are attributes, independent of valuations and the item's attributes, that influence the buyer's offer amount and delay but are unobserved by the econometrician.

Conditional on the seller countering the buyer's first offer, the seller's offer amount and delay, respectively, are

$$p_{k2} = f^{p}_{k2}(p_{k0}, p_{k1}, w_{k1}, \boldsymbol{x}_k, \tilde{B}_k, S_k, \eta^{p}_{k2})$$
$$w_{k2} = f^{w}_{k2}(p_{k0}, p_{k1}, w_{k1}, \boldsymbol{x}_k, \tilde{B}_k, S_k, \eta^{w}_{k2}). \qquad (3)$$

In other words, the seller's offer amount, p_{k2}, and delay, w_{k2}, depend on the past offer amounts (the BIN price and the buyer's first offer), the buyer's delay in the first offer, item attributes, the seller's expectation of the buyer's residual valuation, and the seller's own residual valuation plus analogous η's to the ones in Equation (2).[18]

The buyer's response to the seller's first counteroffer can be expressed as

$$y_{k3} = f^{y}_{k3}(p_{k2}, p_{k1}, p_{k0}, w_{k2}, \boldsymbol{x}_k, B_k, \tilde{S}_k, \eta^{y}_{k3}). \qquad (4)$$

By including only w_{k2} but not w_{k1}, we are implicitly assuming that the delays from the previous rounds do not directly impact the buyer's decision (i.e., after accounting for the seller's delay, the buyer's first offer delay does not further influence the buyer's response). Although w_{k1} does not directly influence the buyer's response, it is still captured by p_{k2} and w_{k2} as demonstrated in Equation (3). Our main focus is on estimating the effect of w_{k2} on y_{k3}.

We standardize the offer amounts p_{k2}, p_{k1}, and p_{k0} by replacing them with the concession weight γ_{kr}. Standardizing the monetary offer amounts via concession weights is consistent with the empirical bargaining literature (e.g., Backus et al. 2020, Larsen et al. 2024, Freyberger and Larsen 2025); nevertheless, this is not without loss of generality because it is an assumption regarding the behavior of the agents.

Recall that the concession weight of the seller's first counteroffer is

$$p_{k2} = \gamma_{k2} p_{k1} + (1 - \gamma_{k2}) p_{k0}. \qquad (5)$$

Therefore, we rewrite Equation (4) as

$$y_{k3} = f^{y}_{k3}(\gamma_{k2}, w_{k2}, \boldsymbol{x}_k, B_k, \tilde{S}_k, \eta^{y}_{k3}). \qquad (6)$$

Also, we rewrite Equation (3) as

$$\gamma_{k2} = f^{\gamma}_{k2}(\gamma_{k1}, w_{k1}, \boldsymbol{x}_k, \tilde{B}_k, S_k, \eta^{\gamma}_{k2})$$
$$w_{k2} = f^{w}_{k2}(\gamma_{k1}, w_{k1}, \boldsymbol{x}_k, \tilde{B}_k, S_k, \eta^{w}_{k2}). \qquad (7)$$

Following the same logic, we can express the seller's response to the buyer's first counteroffer conditional on the buyer countering the seller's first counteroffer, as

$$y_{k4} = f^{y}_{k4}(\gamma_{k3}, w_{k3}, \boldsymbol{x}_k, \tilde{B}_k, S_k, \eta^{y}_{k4}). \tag{8}$$

Again, we make the assumption that the concession weights and delays in previous rounds do not directly impact y_{k4} outside of their influence on γ_{k3} and w_{k3}.

4.3. Endogeneity of Delay and Concession Weights

With this DGP in mind, we can illustrate the sources of endogeneity. We use the buyer's response to the seller's first counteroffer—Equation (6)—as an example, but the arguments apply to the seller's response to the buyer's first counteroffer as well given in Equation (8).

One source of endogeneity is through the messages exchanged by the bargaining parties. Although we observe whether the parties exchanged messages, we do not observe the content of such messages, which can influence the offer amount and delay of the seller's counteroffer via η^{w}_{k2} and η^{γ}_{k2} and the buyer's response through the error term η^{y}_{k3}. This possibility is in accordance with empirical findings that show that the attributes of offers and their responses can be directly impacted by the messages' content (Backus et al. 2025).

Another potential source of endogeneity is product quality that is unobserved by the econometrician but observed by the buyer and the seller, which directly impacts the bargaining parties' decisions. Although we observe some product attributes that are indicative of quality (e.g., item condition and number of photos), we do not observe the product's description, title, or the photos themselves. For example, photos can show different degrees of deterioration or preservation of the product that the simple measure of "new" versus "used" cannot. This unobserved product quality would be captured in η^{y}_{k3}, η^{w}_{k2}, and η^{γ}_{k2}, thus generating endogeneity.

Therefore, to measure the causal effect of delay on bargaining outcomes, we need to address the endogeneity of delay and of the concession weight. We do so through an instrumental variables strategy, which we discuss next.

4.4. Identification Strategy

We describe our identification strategy focusing on how the buyer responds to the seller's first counteroffer, but the same logic applies to the seller's response to the buyer's first counteroffer. For simplicity, we present our identification strategy in terms of the linear specification that we use in our analysis. Because the marginal effect of delay is larger for smaller values of delay, we take the logged value of delay. We specify the structural equation of interest, Equation (6), as

$$y_{k3} = \beta^{w}_{3}\ln(w_{k2}) + \beta^{\gamma}_{3}\gamma_{k2} + \boldsymbol{x}'_k\boldsymbol{\beta}^{x}_{3} + \eta^{y}_{k3}, \tag{9}$$

where β^{w}_{3} is our coefficient of interest. Here, η^{y}_{k3} includes not only unobserved (by the econometrician) product quality but also, the buyer's residual valuation and the buyer's expectation of the seller's residual valuation. We further specify the first-stage regressions, Equation (7), as

$$\begin{aligned}\ln(w_{k2}) &= \alpha^{w}_{2}\ln(w_{k1}) + \alpha^{\gamma}_{2}\gamma_{k1} + \boldsymbol{x}'_k\boldsymbol{\alpha}^{x}_{2} + \eta^{w}_{k2}\\ \gamma_{k2} &= \delta^{w}_{2}\ln(w_{k1}) + \delta^{\gamma}_{2}\gamma_{k1} + \boldsymbol{x}'_k\boldsymbol{\delta}^{x}_{2} + \eta^{\gamma}_{k2}.\end{aligned} \tag{10}$$

As we discussed in Section 4.3, there are potential correlations between η^{y}_{k3} and $(\eta^{w}_{k2}, \eta^{\gamma}_{k2})$, which render $\ln(w_{k2})$ and γ_{k2} endogenous.

Our identification strategy relies on a bargaining party's decisions (i.e., how long to delay and how much to concede) being correlated across negotiations for reasons unrelated to the attributes of the focal negotiation. To show this, we denote the seller's previous negotiation by k'. We write the seller's offer amount and delay in this negotiation as

$$\begin{aligned}\ln(w_{k'2}) &= \alpha^{w}_{2}\ln(w_{k'1}) + \alpha^{\gamma}_{2}\gamma_{k'1} + \boldsymbol{x}_{k'}\boldsymbol{\alpha}^{x}_{2} + \eta^{w}_{k'2}\\ \gamma_{k'2} &= \delta^{w}_{2}\ln(w_{k'1}) + \delta^{\gamma}_{2}\gamma_{k'1} + \boldsymbol{x}_{k'}\boldsymbol{\delta}^{x}_{2} + \eta^{\gamma}_{k'2}.\end{aligned} \tag{11}$$

We propose that $\ln(w_{k'2})$ and $\gamma_{k'2}$ are valid instruments for $\ln(w_{k2})$ and γ_{k2}. Such validity rests on the satisfaction of the following inclusion restriction, an independence condition, and an exclusion restriction. We now address each of them, their interpretation in our setting, and the assumptions that we maintain to ensure that they are satisfied.

4.4.1. Inclusion Restriction. Our inclusion restriction consists of the following maintained assumption; η^{w}_{k2} and η^{γ}_{k2} are composed of an idiosyncratic component and a temporally correlated component. The latter is crucial for the inclusion restriction.

Why is it reasonable to expect that sellers' decisions are temporally correlated, even after accounting for correlations in buyer and seller valuations and item attributes? One such example is the temporal correlation in online activity; if a person spends more time online yesterday, that person is likely to spend more time online today and thus, may be less likely to delay, holding all else constant. The correlation between concession weights in consecutive negotiations has been documented in the existing literature. Send and Serena (2022), who also use these eBay data, found that certain sellers are more "insistent" than others; they tend to repeat the same offer amount multiple times. Furthermore, insistent behavior is "sticky." Sellers who are insistent in the current negotiation are more likely to be insistent in the next negotiation. Insistent or stubborn behavior has also been studied in theoretical models, including Abreu and Gul (2000) and Atakan and Ekmekci (2014). Embrey et al. (2015) posits that insistent behavior can be explained by reputation building or bounded rationality.

We also assume that the correlations in delay are stronger for the same rounds. That is, the seller's decisions in the first counteroffer in k are better predicted by the seller's decisions in the first counteroffer in k' than the second counteroffer in k'. This might occur because the negotiation rounds fundamentally differ. For example, the seller has more information about the buyer after the seller's second counteroffer than the first. For this reason, our instruments are the agent's decisions in the same round.[19] In our empirical analysis in Section 5.1, we show that this inclusion restriction is satisfied.

As mentioned previously, our exposition above describes the instruments for sellers' delay and concession weights, but the logic extends to those of the buyer as well, which correspond to the same negotiation round in a *previous* negotiation with a *different* seller.

4.4.2. Independence Condition. This condition consists of $(w_{k'2}, \gamma_{k'2})$ and η^y_{k3} being independent of each other. In words, the independence condition is that the seller's decisions in negotiation k' are independent of the unobserved (to the econometrician) factors that influence the buyer's response to the seller's counteroffer in negotiation k. In general, this condition is violated if η^y_{k3} is correlated with the determinants of $w_{k'2}$, including $w_{k'1}$ and $\gamma_{k'1}$, the attributes of the item in k', and $(\eta^w_{k'2}, \eta^\gamma_{k'2})$. Next, we describe situations that would cause this independence condition to be violated and how we address them in our analysis.

4.4.2.1. η^y_{k3} is correlated with $x_{k'}$. Controlling for $\boldsymbol{x}_k$ in Equation (9) accounts for this to an extent. However, if the items in k and k' are similar, $\boldsymbol{x}_{k'}$ could remain correlated with η^y_{k3} even after controlling for $\boldsymbol{x}_k$ through the unobserved attribute of the aforementioned product. To address this, we restrict k' to be the previous negotiation for *a different item*. Therefore, we assume that the products in k and k' are uncorrelated in unobserved product attributes. As a robustness check, we further restrict k' to be the previous negotiation for an item in a different product category, assuming that items in different product categories are less likely to have correlated unobserved product attributes.

4.4.2.2. η^y_{k3} is correlated with $(w_{k'1}, \gamma_{k'1})$. The unobserved component of the focal buyer's response might be correlated with the buyer's decisions in k'. This would necessarily be true if negotiations k and k' involved the same buyer. Therefore, we restrict k' to be the seller's previous negotiation with a buyer *different* from the one in k. However, it remains a concern that the residual valuations of buyers are correlated among buyers. We mitigate this concern by including product attributes, buyer fixed effects, and buyers' experience as measured by the number of previous negotiations in which they were involved. However, it is still possible that some correlation arises from the focal seller consistently negotiating with the same type of buyer. We address this by also including seller fixed effects and sellers' experience and ratings. Hence, we assume that after controlling for these variables, the remaining idiosyncratic buyer behavior, such as insistence, is uncorrelated across the buyers who a given seller bargains with. In other words, we assume that the seller does not observe this type of buyer attribute when choosing whether to negotiate.

4.4.2.3. η^y_{k3} is correlated with $(\eta^w_{k'2}, \eta^\gamma_{k'2})$. The η's contain unobserved product attributes and other factors that affect buyer and seller valuations and behavior. As we mentioned above, we maintain the assumption that after controlling for observable product characteristics, unobserved product attributes become uncorrelated, as do buyers' unobservables. Nevertheless, η^y_{k3} can still be correlated $(\eta^w_{k'2}, \eta^\gamma_{k'2})$ if sellers' residual valuations are correlated between items, despite k' involving a different item. We believe that the inclusion of seller fixed effects mitigates this concern. This implies that we assume that there is no residual temporal correlation in sellers' valuations for their different items after controlling for seller fixed effects, experience, ratings, and item attributes.

4.4.3. Exclusion Restriction. The exclusion restriction is that the instruments—the seller's decisions in negotiation k'—do not directly influence y_{k3}, the buyer's outcome in negotiation k. That is, they do not enter Equation (9) directly. We believe that this assumption is reasonable because the buyer in negotiation k is not the same buyer as the one in negotiation k', and the buyer does not observe the seller's decisions in previous negotiations.

4.5. Final Specification

Therefore, our two-stage least-squares (2SLS) specification for the effect of delay on the other agent's response is

$$y_{k,r+1} = \beta^w_r \ln(w_{kr}) + \beta^\gamma_r \gamma_{kr} + \boldsymbol{x}'_k \boldsymbol{\beta}^x_r + \epsilon^y_{k,r+1} \tag{12}$$

$$\ln(w_{kr}) = \alpha^w_r \ln(w_{k'r}) + \alpha^\gamma_r \gamma_{k'r} + \boldsymbol{x}'_k \boldsymbol{\alpha}^x_r + \epsilon^w_{kr} \tag{13}$$

$$\gamma_{kr} = \delta^w_r \ln(w_{k'r}) + \delta^\gamma_r \gamma_{k'r} + \boldsymbol{x}'_k \boldsymbol{\delta}^x_r + \epsilon^\gamma_{kr}, \tag{14}$$

where Equations (13) and (14) are the first-stage regressions and Equation (12) is the second-stage regression. In these regressions, delay is measured in hours.

The vector $\boldsymbol{x}$ contains the relevant observed negotiation-level characteristics: the seller's feedback score (logged) and experience (logged), the buyer's experience (logged), and the number of photos included in the listing; indicators of whether the BIN price was a round number and whether messages were exchanged; and fixed effects for the seller, buyer, category, item condition, year-month, and day of the week. Therefore, the assumptions that we maintain regarding unobserved product attributes and the buyer's and the seller's residual valuations are conditional on all of these variables.

The dependent variable y denotes the other party's response (indicators of accept, counter, or decline) and conditional on countering, the other party's concession weight. We also measure the effect on the outcomes of the thread: whether the item was ultimately sold in thread k; the ratio of the final price over the opponent's previous offer conditional on being sold in thread k; and the length of the negotiation (i.e., total number of rounds in the thread).

There is an important limitation that arises because of our choice of instruments. In order for a negotiation to have instruments, the bargaining agent must have had a previous negotiation with a different opponent for a different product. In this seller counteroffer data set, 66% of sellers and 93% of observations meet these criteria. In the buyer counteroffer data set, 25% of buyers and 42% of observations meet these criteria. This limits our effects to apply only to this subset of agents. In other words, our effects cannot be generalized to buyers and sellers in their first negotiation on eBay.

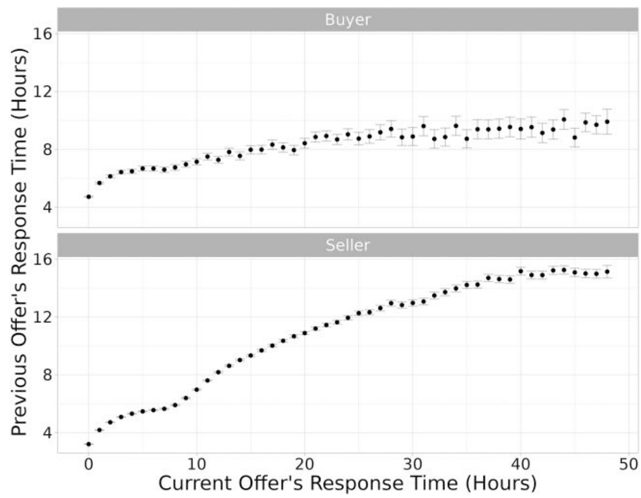
5. Results

We now present the results of our empirical analysis. First, we provide evidence that the inclusion restriction discussed in Section 4.4.1 is satisfied. Second, we present the estimates of Equation (12) using our proposed instrumental variables strategy; for reference, we also provide the estimates obtained from ordinary least squares (OLS). Third, we present results from a series of exercises that demonstrate main estimates as robust to the use of alternative criteria for the construction of our instrumental variables and of specific subsamples of the data.

5.1. Verifying Inclusion Restriction

We verify that the instruments are strong; the partial F statistics are large (>300), and the inclusion of the instruments improves the fit in the first stage. The partial F statistics and the incremental R^2 of the first stage are reported in Table D.5 in the Online Appendix. We also report the raw data correlations between the instruments and the endogenous variables. Figure 4 shows that there is a positive correlation between delay in thread k and k'. More specifically, it plots the average delay in the previous negotiation for each bucket of delay in the current negotiation.[20] We do a similar exercise for the concession weights in negotiations k and k' and again, find a positive correlation, which is displayed in Figure 5.[21]

Figure 4. Correlation Between the Response Time for the Current Offer and the Previous Negotiation Offer

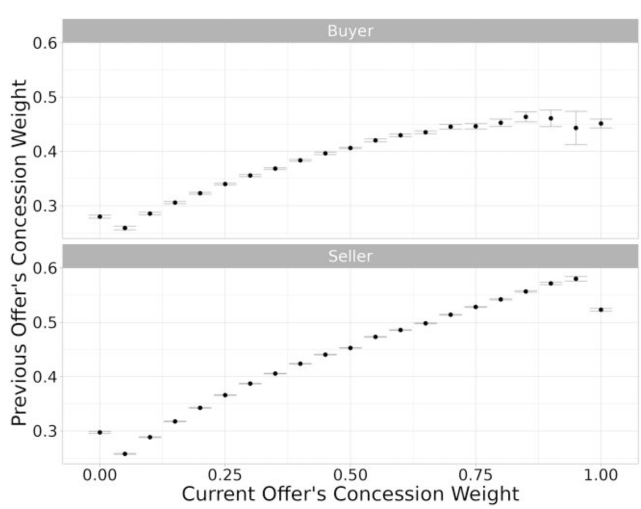


Notes. This figure plots the correlation between the endogenous variable, delay, and its instrument. The x axis is the bargaining party's response time for an offer rounded to the nearest hour. The y axis is the instrument—the bargaining party's response time for their offer in their previous negotiation. The error bars represent the 95% confidence intervals.

5.2. Main Results

We now present the results of the regressions. We discuss interpretation of the results and their potential mechanisms in Section 6.

Figure 5. Correlation Between the Concession Weight for the Current Offer and the Previous Negotiation Offer



Notes. This figure plots the correlation between the endogenous variable, γ, and its instrument. The x axis is the bargaining party's concession weight for an offer rounded to the nearest 0.05. The y axis is the instrument—the bargaining party's concession weight for their offer in their previous negotiation. The error bars represent the 95% confidence intervals.

Table 3. Effect of Seller Delay on Buyer Responses: OLS and 2SLS Estimates

	Accept		Counter		Decline	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Delay (log)	−0.0010***	−0.0035***	−0.0168***	−0.0165***	0.0168***	0.0189***
	(9.62×10^{-5})	(0.0009)	(0.0001)	(0.0012)	(0.0001)	(0.0014)
Concession Weight	0.4546***	0.2259***	−0.0525***	0.0509**	−0.3937***	−0.3460***
	(0.0024)	(0.0167)	(0.0019)	(0.0219)	(0.0022)	(0.0243)
Observations	4,976,903	4,976,903	4,976,903	4,976,903	4,976,903	4,976,903
R^2	0.478	0.470	0.411	0.410	0.432	0.431
DV mean	0.146	0.146	0.263	0.263	0.561	0.561

Notes. This table reports only the coefficients of the endogenous variables. See Table D.6 in the Online Appendix for the coefficients of all variables. *Delay* is measured in hours. All specifications include buyer, seller, category, year-month, day of the week, and item condition fixed effects plus the number of photos of the item, indicators of whether the BIN price was a round number and of whether the buyer and the seller exchanged messages, seller ratings and experience, and buyer experience. Standard errors are clustered at the seller level. There are 262,399 clusters. DV, dependent variable.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

We start with the effect of seller delay on the likelihood that the buyer accepts, counters, or declines. Table 3 reports both the OLS and 2SLS estimates. Recall that the sample in Table 3 consists of only the buyer's response to the seller's first counteroffer (round 2). We find that seller delay has a statistically significant and negative effect on the likelihood that the buyer counters. We interpret the magnitudes relative to the average seller delay, which is 5.4 hours. On average, doubling the seller's delay (e.g., increasing delay by 5.4 hours) decreases the probability of the buyer countering by 6.3% (or 1.7 percentage points). We also find statistically significant effects on the likelihood that the buyer accepts or declines; doubling the seller's delay decreases the probability that the buyer accepts by 2.4% (0.35 percentage points) and increases the probability that they decline by 3.3% (1.9 percentage points). We find that the 2SLS estimate of the effect on delay is fairly similar to the OLS estimate.

Table 4 presents the effect of seller delay on downstream outcomes. The dependent variable in columns (1) and (2) in Table 4 is the buyer's concession weight of the counteroffer conditional on countering. We do not find a significant effect of seller delay on the buyer's concession in the next offer conditional on the buyer counteroffering. Columns (3) and (4) in Table 4 report the effect on the number of total negotiation rounds. The longer the seller delays, the fewer rounds

Table 4. Effect of Seller Delay on Thread Outcomes: OLS and 2SLS Estimates

	Opponent's next γ		*N* rounds		Sold		Sold: Offer ratio	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delay (log)	0.0030***	0.0015	−0.0323***	−0.0353***	−0.0080***	−0.0132***	0.0029***	0.0054***
	(0.0001)	(0.0010)	(0.0003)	(0.0028)	(0.0001)	(0.0012)	(0.0002)	(0.0015)
Concession Weight	0.1313***	0.1014***	−0.3022***	−0.1125**	0.5775***	0.3345***	−0.6076***	−0.0022
	(0.0022)	(0.0199)	(0.0042)	(0.0501)	(0.0025)	(0.0218)	(0.0041)	(0.0395)
Observations	996,946	996,946	4,976,903	4,976,903	4,976,903	4,976,903	1,145,843	1,145,843
R^2	0.597	0.597	0.394	0.394	0.469	0.463	0.644	0.572
DV mean	0.367	0.367	2.558	2.558	0.3	0.3	1.286	1.286

Notes. Columns 1 and 2 includes only threads in which the opponent's response was to counter. Columns 3–6 include all threads, and columns 7 and 8 include only threads in which the item was ultimately sold. The dependent variables are the concession weight of the opponent's next offer (conditional on the opponent countering), the number of rounds that the negotiation takes to resolve, an indicator for whether the item is ultimately sold in this negotiation, and final selling price divided by the price of the buyer's first offer (conditional on being sold in this negotiation). This table reports only the coefficients of the endogenous variables. *Delay* is measured in hours. All specifications include buyer, seller, category, year-month, day of the week, and item condition fixed effects plus the number of photos of the item, indicators of whether the BIN price was a round number and of whether the buyer and the seller exchanged messages, seller ratings and experience, and buyer experience. Standard errors are clustered at the seller level. Columns 1 and 2 have 121,883 clusters, columns 3–6 have 262,399 clusters, and columns 7 and 8 have 127,991 clusters. Table D.7 in the Online Appendix reports the coefficients for all variables. DV, dependent variable.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 5. Effect of Buyer Delay on Seller Responses: OLS and 2SLS Estimates

	Accept		Counter		Decline	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Delay (log)	0.0103***	0.0130***	−0.0112***	−0.0210***	0.0007**	0.0068**
	(0.0003)	(0.0031)	(0.0004)	(0.0037)	(0.0003)	(0.0031)
Concession Weight	0.8750***	0.8145***	−0.4286***	−0.5248***	−0.4474***	−0.2930***
	(0.0047)	(0.0364)	(0.0052)	(0.0427)	(0.0043)	(0.0364)
Observations	587,777	587,777	587,777	587,777	587,777	587,777
R^2	0.561	0.561	0.506	0.505	0.511	0.509
DV mean	0.281	0.281	0.481	0.481	0.227	0.227

Notes. This table reports only the coefficients of the endogenous variables. See Table D.11 in the Online Appendix for the coefficients for all variables. All specifications include buyer, seller, category, year-month, day of the week, and item condition fixed effects plus the number of item photos, seller ratings, seller experience, buyer experience, and indicators of whether the BIN price was a round number and of whether the parties exchanged messages. Standard errors are clustered at the buyer level. There are 123,947 clusters. DV, dependent variable.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

the negotiation takes to resolve. Furthermore, on average, doubling seller delay results in a 4.4% (1.3-percentage-point) decrease in the probability that the item will be sold to that buyer (columns (5) and (6) in Table 4). Conditional on being sold, the item sells for a 0.4% higher price relative to the buyer's first offer (columns (7) and (8) in Table 4), equivalent to approximately $0.74.[22]

Next, we focus on the effect of the *buyer's* delay on the *seller's* decisions, presented in Table 5. The sample in Table 5 consists only of the seller's response to the buyer's first counteroffer (round 3). We find that the longer the buyer delays, the less likely the seller is to counter (columns (3) and (4) in Table 5). On average, doubling buyer delay decreases the probability that the seller counters by 3.6% (1.7 percentage points).

Buyer delay also significantly increases the probability that the seller accepts and declines; doubling buyer delay increases the probability that the seller accepts by 5% (1.4 percentage points) and the probability that the seller declines by 3% (0.86 percentage points).

Table 6 displays the effect of buyer delay on outcomes. We find that buyer delay significantly reduces the number of total rounds in the thread. However, we do not find any significant effects on the seller's counteroffer conditional on countering, the probability that the item is sold in the focal thread, or the ratio of the selling price over the seller's previous offer conditional on selling. Note that the longer the buyer delays, the more likely the seller is to accept, thereby increasing the probability that the item is sold in the focal thread. However, there is no average effect on the probability

Table 6. Effect of Buyer Delay on Thread Outcomes: OLS and 2SLS Estimates

	Opponent's next γ		*N* rounds		Sold		Sold: Offer ratio	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delay (log)	0.0020***	0.0006	−0.0284***	−0.0359***	−0.0022***	0.0006	−0.0028***	−0.0007
	(0.0003)	(0.0039)	(0.0008)	(0.0073)	(0.0004)	(0.0035)	(0.0001)	(0.0015)
Concession Weight	0.1615***	0.0488	−0.9570***	−0.9059***	0.8926***	0.7352***	0.1926***	0.2098***
	(0.0044)	(0.0687)	(0.0100)	(0.0828)	(0.0048)	(0.0402)	(0.0018)	(0.0172)
Observations	234,214	234,214	587,777	587,777	587,777	587,777	235,314	235,314
R^2	0.590	0.587	0.493	0.493	0.568	0.567	0.705	0.704
DV mean	0.234	0.234	3.848	3.848	0.478	0.478	0.867	0.867

Notes. Columns 1 and 2 includes only threads in which the opponent's response was to counter. Columns 3–6 include all threads, and columns 7 and 8 include only the threads in which the item was ultimately sold. The dependent variables are the concession weight of the opponent's next offer (conditional on the opponent countering), the number of rounds that the negotiation takes to resolve, an indicator for whether the item is ultimately sold in this negotiation, and final selling price divided by the price of the seller's first counteroffer (conditional on being sold in this negotiation). For readability, this table reports only the coefficients of the endogenous variables. All specifications include buyer, seller, category, year-month, day of the week, and item condition fixed effects plus the number of photos of the item, indicators of whether the BIN price was a round number and whether the buyer and the seller exchanged messages, seller ratings and experience, and buyer experience. Standard errors are clustered at the buyer level. Columns 1 and 2 have 63,385 clusters, columns 3–6 have 123,947 clusters, and columns 7 and 8 have 63,997 clusters. Table D.12 in the Online Appendix reports the coefficients for all variables. DV, dependent variable.
****$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

that it is sold (columns (5) and (6) in Table 6). This null average effect occurs because of a reduction in the probability that the item is sold in the thread conditional on the seller countering or declining.[23]

5.3. Robustness

We conduct several robustness checks to support the estimates' credibility. First, we wish to rule out any concern that the content of the messages exchanged by the bargaining parties might reveal valuations or other private information correlated with delay. Therefore, we conduct a robustness check in which we estimate the effects of delay only for offers in which the offering party did not send a message. In our sample, 72% (77%) of seller (buyer) counteroffers do not include a message. We find that the effects are robust to threads with no messages.[24]

Another confounder can be concurrent threads. For example, bargaining for multiple items at the same time can impact both delay and valuations. To rule this out, we estimate the 2SLS regression only for threads in which neither the buyer nor the seller is actively involved in another thread (i.e., have no concurrent threads). The percentage of those threads in our sample is 62% for seller counteroffers and 61% for buyer counteroffers. Again, we find that the effects are robust to eliminating concurrent threads.[25]

Lastly, valuations for similar items may be correlated, which would violate the validity of the instrument. Assuming that valuations for items across different categories are less likely to be correlated, we modify the instrument to be the bargaining party's delay and concession weight from the previous negotiation with a different opponent for a product in a different category.[26] We find similar results to the main specification.[27]

We also conduct another robustness check that includes product ID fixed effects. The product ID is an anonymous identifier for the product type itself (e.g., an iPhone 12), which is available only for products that can be linked to a specific catalog. Including such fixed effects can control for unobserved product attributes that might be correlated with buyer and seller valuations. Our results are robust to the inclusion of product ID fixed effects. Estimates are reported in Table D.18 in the Online Appendix. The estimates are also robust to controlling for the logged reference price.[28]

In addition, we find that the effects of delay are robust to relatively short periods of delay (below-average delay) and when the stakes are relatively lower (low BIN prices); these are conditions where one may expect that delay is less important. Panel A of Table 7 and panel A of Table 8 present the 2SLS estimates for the effect of seller and buyer delay on

Table 7. 2SLS Estimates of the Effect of Seller Delay: Small Delay and Low Prices

Variable	Accept (1)	Counter (2)	Decline (3)	Sold (4)	Sold: Offer ratio (5)
			Panel A: Below-average delay (5.4 hours)		
Delay (log)	−0.0043*	−0.0115***	0.0193***	−0.0125***	0.0062*
	(0.0022)	(0.0030)	(0.0033)	(0.0029)	(0.0037)
Concession Weight	0.2206***	0.0692**	−0.3464***	0.3593***	−0.0268
	(0.0209)	(0.0283)	(0.0310)	(0.0279)	(0.0492)
Observations	3,222,327	3,222,327	3,222,327	3,222,327	749,643
R^2	0.502	0.447	0.465	0.497	0.613
DV mean	0.147	0.282	0.54	0.311	1.284
			Panel B: Low BIN prices (less than $29)		
Delay (log)	−0.0002	−0.0218***	0.0216***	−0.0138***	0.0029
	(0.0022)	(0.0025)	(0.0028)	(0.0026)	(0.0029)
Concession Weight	0.3656***	−0.1226*	−0.2953***	0.4046***	−0.0471
	(0.0605)	(0.0654)	(0.0760)	(0.0725)	(0.0908)
Observations	1,051,934	1,051,934	1,051,934	1,051,934	332,291
R^2	0.553	0.506	0.517	0.532	0.632
DV mean	0.227	0.24	0.519	0.397	1.343

Notes. Panel A limits the sample to only offers where seller delay is within 5.4 hours, and panel B limits the sample to only threads where the BIN price is less than U.S. $29, the first quartile of BIN prices in the sample. All specifications include the same controls as above. Standard errors are clustered at the seller level. In panel A, the number of clusters in the first four columns is 214,467, and the number of clusters in the last column is 98,974. In panel B, the number of clusters in the first four columns is 69,448, and the number of clusters in the last column is 37,942. DV, dependent variable.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 8. 2SLS Estimates of the Effect of Buyer Delay: Small Delay and Low Prices

Variable	Accept (1)	Counter (2)	Decline (3)	Sold (4)	Sold: Offer ratio (5)
Panel A: Below mean delay (6.1 hours)					
Delay (log)	0.0073	−0.0298***	0.0195***	0.0014	0.0022
	(0.0071)	(0.0086)	(0.0074)	(0.0080)	(0.0033)
Concession Weight	0.8549***	−0.5916***	−0.2679***	0.7610***	0.2177***
	(0.0554)	(0.0659)	(0.0569)	(0.0624)	(0.0291)
Observations	394,868	394,868	394,868	394,868	154,760
R^2	0.594	0.540	0.547	0.601	0.727
DV mean	0.269	0.492	0.227	0.478	0.871
Panel B: Low BIN prices (less than $29)					
Delay (log)	−0.0035	−0.0281**	0.0319***	−0.0345***	−0.0017
	(0.0125)	(0.0132)	(0.0119)	(0.0133)	(0.0057)
Concession Weight	0.8215***	−0.9035***	0.0577	0.5995***	0.1910***
	(0.1542)	(0.1648)	(0.1501)	(0.1637)	(0.0685)
Observations	112,284	112,284	112,284	112,284	58,217
R^2	0.631	0.592	0.590	0.617	0.730
DV mean	0.382	0.395	0.218	0.597	0.853

Notes. This table is analogous to Table 7 but for buyer delay on seller outcomes. Standard errors are clustered at the buyer level. In panel A, the number of clusters in the first four columns is 91,546, and the number of clusters in the last column is 45,645. In panel B, the number of clusters in the first four columns is 28,751, and the number of clusters in the last column is 16,624. DV, dependent variable.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

buyer and seller responses, respectively, for threads with below-average delay, which is 5.4 hours for sellers and 6.1 hours for buyers. The estimates are similar to those using the full sample, indicating that even short periods of delay impact bargaining decisions and negotiation outcomes. One difference is that in response to delay, the other party is more likely to switch from countering to declining in this subsample compared with the full sample.

Similarly, we consider a bargaining thread to be lower stakes for lower-priced products as opposed to higher-priced goods. Therefore, we consider only bargaining threads for listings where the item has a BIN price in the first quartile of our sample (less than or equal to $29). The estimates of this regression are displayed in panel B of Table 7 and panel B of Table 8. Again, we find similar effects of delay for negotiations over goods with low prices as with the entire sample with the same exception; buyers are more likely to switch to declining for goods with low prices.

6. Mechanisms

In summary, we find that the longer the seller delays in responding to the buyer's first offer, the less likely the buyer will respond to the seller's eventual offer by countering. The same is true for buyer delay. This negative effect of delay on countering is robust to short periods of delay and lower-stakes bargaining. The effects of delay on whether the other party accepts or declines differ by seller and buyer delay. The longer the seller delays, the more likely the buyer is to switch from countering to declining; the longer the buyer delays, the more likely the seller is to switch from countering to accepting. This also leads to differences in bargaining outcomes. The empirical effects on all outcomes are summarized in Table 9. Next, we consider the mechanisms that can drive these effects.

Table 9. Summary of Empirical Findings

Variable	Counter	Accept	Decline	Pr(sale)	$\frac{\text{End price}}{\text{previous offer}}\mid\text{sale}$
Seller delay	↓ 6%	↓ 2%	↑ 3%	↓ 4%	↑ 0.5%
Buyer delay	↓ 4%	↑ 5%	↑ 3%	—	—

Notes. The magnitudes of the effect are from doubling seller or buyer delay. For sellers, the average delay is 5.4 hours, and for buyers , the average delay is 6.1 hours. The last column displays the ratio of the final price to the opponent's previous offer conditional on a sale.

6.1. Delay as a Signal

A potential mechanism behind our empirical effects is that delay acts as a signal of the delaying party's bargaining power or valuations. To our knowledge, the main theoretical papers that model strategic delay in negotiations with alternating offers are Admati and Perry (1987) and Cramton (1992). Our setting is closest to that of Cramton (1992), which considered a setting with two-sided incomplete information.[29] For this reason, we focus on Cramton (1992) to describe this mechanism.

Under the setup of Cramton (1992), seller and buyer valuations of a product, S and B, respectively, are independently drawn from a common distribution, $F(\cdot)$. The two parties are risk neutral, their preferences satisfy a typical single-crossing property, and they share a common discount rate r. Cramton (1992) shows that there exists and characterizes a sequential equilibrium in this game that gives important predictions regarding the role of delay.

In this equilibrium, delay acts as a signal of a party's valuation and relates to the gains from trade, $B-S$. Parties that expect higher gains from trade delay less because discounting impacts their expected outcomes more intensely. In other words, parties with larger gains from trade have more to lose from delay because of time discounting. Hence, the model predicts that buyers with high valuations and sellers with low valuations are less willing to delay. Delay acts as the sole signal of valuations because as Cramton (1992) argues, "it is a more efficient signal of strength" than price as "it is easier for low-valuation sellers to imitate the price behaviour of high-valuation sellers" (Cramton 1992, p. 207).

The predictions that buyers with high valuations and sellers with low valuations are less willing to delay have the following implications for the other party's outcomes. Sellers with high valuations are less likely to accept a given offer than sellers with lower valuations. Thus, when a buyer infers that a seller has a high valuation, the buyer infers that the seller is unlikely to negotiate further, reducing the likelihood that the buyer counters after observing the signal for the seller's high valuation. The same logic is true for buyers with low valuations; buyers with low valuations are unlikely to accept a higher price, so the seller is less likely to continue bargaining after observing that the buyer has a low valuation. In short, if delay is a signal that the seller (buyer) has lower gains from trade, then the buyer (seller) should be less likely to counter as the delay increases. Our empirical findings are consistent with this prediction.

In addition, the model predicts that conditional on being successful, sellers with high valuations should obtain higher transaction prices, whereas buyers with low valuations should obtain lower transaction prices. Consequently, increases in seller and buyer delay should lead to higher and lower transaction prices, respectively. The significant results shown in columns (7) and (8) in Table 4 confirm the former prediction; however, the analogous effects for buyer delay are not significant as shown in columns (7) and (8) in Table 6.

Furthermore, an implication of this mechanism is that delay should have a smaller effect when the receiving party believes that delay is not strategic. For example, taking eight hours to respond to an offer that is submitted at 12 a.m. (because the receiving party is likely to be asleep) is less informative than taking eight hours to respond to an offer that was submitted at 5 p.m. (when the receiving party is more likely to be active). We indeed find this to be true in our data; longer periods of delay (greater than six hours) have a significantly smaller in magnitude effect on the other party's response when the original offer was sent during off-peak hours (12 a.m. to 5 a.m.) than during peak hours. We describe these results in detail in Online Appendix C.[30]

Another implication of this mechanism is that sellers who delay more have higher valuations and that buyers who delay more have lower valuations. We cannot perfectly test this implication because we do not observe valuations. However, we can verify whether the correlations between delay and user and negotiation attributes are consistent with this implication. We do so by estimating the following linear regressions:

$$\ln(w_{k2}) = z'_{k2}\boldsymbol{\delta}^z_2 + \nu_{k2} \tag{15}$$

$$\ln(w_{k3}) = z'_{k3}\boldsymbol{\delta}^z_3 + \nu_{k3}. \tag{16}$$

Equations (15) and (16) examine seller and buyer delay, respectively. The $\boldsymbol{\delta}$'s are the coefficients to be estimated, and the ν's are error terms. The vector $\boldsymbol{z}$ contains the previously defined vector $\boldsymbol{x}$ with the addition of more variables. In particular, we add to the vector z_{k2}: an indicator of whether the focal user has another active thread at the same time as the focal thread (has concurrent thread), the previous offer's delay (logged) and concession weight, the logarithm of the number of other listings in the same category as the focal item (N listings in category), and the average selling price of similar listings relative to the focal listing's BIN price.[31]

The model from Cramton (1992) suggests a positive correlation between sellers' valuations and delay. We can examine the relationship between seller delay and the BIN price, which is weakly increasing with the seller's valuation in several models.[32] To account for differences in products, we focus on the BIN price relative to the price of similar goods. In the data provided by Backus et al. (2020), the price of similar items is reported as the "reference price," which is defined as the average price for fixed-price listings with the same listing title as the focal item that was sold during the time frame of the data.

Analogously, Cramton (1992) predicts a negative correlation between buyers' valuation and delay. We can examine the relationship between buyers' first offer and delay instead, maintaining the assumption that the buyer's first offer is increasing in the buyer's valuation.[33] Again, to account for differences in products, we normalize the buyer's first offer price with the reference price. Therefore, the vector z_{k3} includes the vector z_{k2} with the addition of the buyer's first offer relative to the reference price ratio.

Column (1) in Table 10 displays the OLS estimates of Equation (15). As expected, sellers delay more if they have concurrent threads. They also take longer to respond to less-experienced buyers with low initial offers. Most importantly, sellers delay more in responding to the buyer's initial offer for listings with higher BIN prices, especially if the price is higher relative to similar products, as evidenced by the statistically significant positive coefficient for the BIN price to reference price ratio. This correlation is consistent with sellers with higher valuations delaying more.

Table 10. OLS Estimates of Equations (15) and (16)

	Delay (log)	
Variable	Sellers (1)	Buyers (2)
Seller Feedback Score (log)	0.0520*** (0.0098)	0.0135 (0.0150)
Previous Offer's Concession Weight	−0.1283*** (0.0147)	−0.0413* (0.0211)
Previous Offer's Delay (log)	0.0484*** (0.0015)	0.3482*** (0.0018)
BIN Price is Round	0.0245*** (0.0081)	−0.0567*** (0.0169)
Has Message	−0.0717*** (0.0045)	−0.1434*** (0.0090)
# Photos	−0.0002 (0.0009)	0.0003 (0.0019)
BIN Price (log)	0.0098*** (0.0024)	0.1928*** (0.0147)
Seller Experience (log)	−0.0428*** (0.0038)	−0.0128* (0.0076)
Buyer Experience (log)	−0.0012 (0.0042)	−0.0640*** (0.0097)
Has Concurrent Thread	0.0567*** (0.0036)	−0.0713*** (0.0072)
N Listings in Category (log)	−0.0017 (0.0013)	−0.0015 (0.0029)
BIN to Ref Price Ratio	0.0158*** (0.0052)	0.0592*** (0.0169)
Buyer's 1st Offer to Ref Price Ratio (log)		−0.1630*** (0.0149)
Standard errors	Seller	Buyer
Observations	3,670,067	777,558
R^2	0.505	0.637

Notes. Samples include observations only for which the reference price is observed, and the reference price is less than the 99.5th percentile (3.3). Both specifications include fixed effects for the seller, buyer, category, item condition, year-month, and day of week. The unit for delay is hours. Standard errors are clustered by sellers (281,194 clusters) and buyers (220,442 clusters).

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The estimates of Equation (16) are displayed in column (2) in Table 10. We expect that buyers with lower valuations make lower offers relative to the price of similar goods. Therefore, if buyers with lower gains from trade (i.e., lower valuations) are more patient and thus, delay more, then the correlation between the first offer amount relative to the reference price and buyer delay should be negative. Indeed, we find a negative correlation, which is shown by the coefficient of "*Buyer's 1st Offer to Ref Price Ratio* (log)" in column (2) in Table 10.

In summary, our empirical findings on the effects of delay on the other party's responses and when buyers and sellers choose to delay are consistent with a model of strategic delay, in which delay acts as a signal for the offering party's valuations. Nevertheless, it is important to emphasize that this does not mean that valuations are the true source of the effects of delay that we estimate; the directions of these effects are also consistent with other explanations, such as delay signaling bargaining power more generally.

However, it is also important to note that the stylized setting in Cramton (1992) has important differences from ours. First, in Cramton (1992), the party that makes the initial offer is determined endogenously, whereas in our setting, the party that makes an offer in a given round is determined by eBay's rules (the seller selects a buy it now price, and the buyer submits the first offer). Second, in the equilibrium in Cramton (1992), negotiations should be resolved after at most two offers if there are gains from trade. In our data, 13.7% of successful negotiations take three or more offers to resolve, which is inconsistent with this prediction. This inconsistency is also noted in Backus et al. (2020).[34] Furthermore, at the time of data collection, offers on eBay expired after 48 hours; time discounting might not be a realistic description of this environment. Instead, there are other factors that could generate similar effects of delay and also, might be more realistic, such as risk aversion or a different form of impatience generated: for example, by private deadlines as in Coey et al. (2020).

In light of these differences between our setting and that of Cramton (1992) and the fact that we cannot observe agents' intentions, we cannot definitively identify whether delay is strategic and motivated by signaling considerations. We can only provide a potential explanation and demonstrate that the predictions about the effects of delay under this model of delay as a signal are consistent with empirical patterns.

6.2. Effects on Accepting and Declining

The signaling mechanism as implied by Cramton (1992) yields precise predictions regarding the relationships between buyer and seller delay and the probability that the opposing party counters. However, this mechanism does not provide us with results regarding the probabilities of acceptance and rejection of offers. Below, we propose a potential mechanism that can explain our findings regarding acceptances and declines.

Recall that we find an asymmetric effect between buyers and sellers on whether they accept or decline in response to delay; when the seller delays longer, the buyer substitutes from countering to *declining*, whereas when the buyer delays longer, the seller substitutes from countering to *accepting*.[35] We hypothesize that these asymmetric effects can occur if, on average, buyers have lower valuations than sellers, buyers have higher outside options, or sellers are less patient than buyers. All of these potential explanations rely on bargaining agents to be forward looking and imply that buyers tend to have greater bargaining power than sellers. To illustrate the intuition behind why these differences in sellers and buyers can explain this result, we provide a simple model of buyer and seller decision making.

6.2.1. Buyers' Responses to Seller Delay. Consider a buyer's utility from accepting, countering, and declining a seller's offer of p in negotiation k. Let w denote the seller's delay and B_k denote the buyer b's valuation of the item under negotiation k. The buyer's utilities from accepting, countering, and declining the seller's offer are the following:

$$u_{bk} = \begin{cases} B_k - p & \text{if accept} \\ \Pr(\text{agree}) \cdot (B_k - \mathbb{E}[p|w]) + \{1 - \Pr(\text{agree})\} \cdot U_{b,k+1} - c & \\ & \text{if counter} \\ U_{b,k+1} & \text{if decline,} \end{cases} \tag{17}$$

where Pr(agree) is the buyer's expected probability that the buyer will come to an agreement with the seller; $\mathbb{E}[p|w]$ is the buyer's expectation of the agreed-upon price conditional on the seller's delay w; $k+1$ denotes the next negotiation; and $U_{b,k+1}$ is the buyer's expected utility from continuing to the next negotiation. For simplicity, we implicitly assume that the buyer looks ahead only one period (i.e., the next negotiation) and that $\mathbb{E}[p|w]$ depends only on w, even though in reality, the expected agreed-upon price also depends on the item's attributes, etc. Furthermore, we assume that creating counteroffers is costly, which we represent with the cost c. The expected value of the future negotiation, $U_{b,k+1}$, is a reduced-form object that depends on several factors, including the buyer's impatience, the buyer's expected intrinsic valuation of the item under negotiation $k+1$, and the probability that the buyer will find another seller to negotiate with.

The relative order of the utilities determines which actions the buyer substitutes from. That is, when the utility from countering decreases, the buyer will choose the action that yields the next-highest utility. In our data, the mean probabilities that a buyer accepts, counters, or declines are 15%, 26%, and 56%, respectively (see the "DV mean" row in Table 3). These suggest that, on average, $u_{bk}(\text{decline}) > u_{bk}(\text{counter}) > u_{bk}$ (accept). Based on Cramton (1992), we would expect that when the buyer observes a long delay, the buyer infers that the seller has a high valuation, meaning that it will be more difficult to reach a lower agreed-upon price (Pr(agree) goes down, and $\mathbb{E}[p|w]$ goes up). Therefore, $u_{bk}(\text{counter})$ decreases, and $u_{bk}(\text{decline})$ becomes even more likely to be the best option, leading to more buyers choosing to decline rather than counter.

6.2.2. Sellers' Responses to Buyer Delay. The seller's relative utilities from accepting, countering, and declining are similar to the buyer's. Denoting the seller's valuation with S_k, it follows that

$$u_{sk} = \begin{cases} p - S_k & \text{if accept} \\ \Pr(\text{agree}) \cdot (\mathbb{E}[p|w] - S_k) + \{1 - \Pr(\text{agree})\} \cdot U_{s,k+1} - c & \\ & \text{if counter} \\ U_{s,k+1} & \text{if decline,} \end{cases} \tag{18}$$

where the objects defined in Equation (18) are analogous to those in Equation (17). The mean probabilities that a seller accepts, counters, or declines are 29%, 48%, and 22%, respectively ("DV means" row in Table 5), which imply $u_{sk}(\text{counter}) > u_{sk}(\text{accept}) > u_{sk}(\text{decline})$ on average. Based on the results from Cramton (1992), when the buyer delays, the seller infers that the buyer has a low valuation; therefore, the chance of agreement and the agreed-upon price will be lower, and so, $u_{sk}(\text{counter})$ decreases. If the decrease is large enough, then the seller will switch from countering to the option that yields the next-highest utility (accepting), which is what we observe empirically.

Why might sellers prefer countering to accepting to declining, whereas buyers prefer declining to countering to accepting? A possible explanation is that $U_{b,k+1} \gg U_{s,k+1}$; in other words, the outside option is higher for buyers than for sellers. This can result from holding all else constant, buyers having lower intrinsic valuations for the products than sellers on average. This can also be because of differences in beliefs about the likelihood of finding another bargaining party with whom to negotiate. That is, buyers might be more likely to find another seller who has a similar product than sellers are to get an offer from another buyer.[36] Another possible explanation is that sellers are more impatient than buyers. All of these explanations imply that sellers would rather try to come to an agreement in the current negotiation (accept or counter) than pursue a future negotiation with another buyer should the opportunity arise. Conversely, buyers have higher outside options, have lower valuations, or are more patient, so they would prefer to decline (and move on to the next negotiation) rather than spending effort to come to an agreement in the negotiation at hand.

Buyers having better outside options than sellers is also consistent with another empirical pattern that we observe; when the seller concedes more, the buyer is more likely to counter, but when the buyer concedes more, the seller is less likely to counter.[37] This result, which can be seen from the coefficients of the concession weight in Tables 3 and 5, is consistent with the idea that if a buyer sees that a seller concedes more, the buyer will counter again to try to get a better deal. The buyer might do so because the outside option is high, so the buyer is willing to take a higher risk that this negotiation fails. Conversely, once the buyer concedes more, the seller will accept instead of counter because the seller would prefer seeing the negotiation succeed over the negotiation's failure if the buyer counters.

Like the other mechanisms, we cannot test whether sellers and buyers differ in their valuations, outside options, or levels of patience in this data set. This limitation arises partly because we lack detailed attributes about the products or users. For instance, if we could observe deadlines for products (e.g., sporting event tickets), we might infer impatience. Likewise, knowing the number of substitute products available during a negotiation could serve as a proxy for outside options. Consequently, we defer a formal test of this hypothesis to future research.

6.2.3. Buyers' Loss of Interest over Time. Another possible explanation for why buyers switch from countering to declining when sellers delay is that the longer a seller takes to respond, the more likely the buyer is to lose interest in this seller's item. This notion relates to the previous explanation that buyers have higher outside options than sellers, in which case they are more prone to losing interest compared with sellers. This loss of interest can be because of the buyer purchasing from or bargaining with another seller for a similar item, perhaps even off of the platform.[38] Unfortunately, we do not have data on off-platform purchases, so we cannot verify this.

7. Conclusion

This paper measures the causal effects of delay in bilateral bargaining with two-sided incomplete information using data from millions of negotiations on eBay. We find that the longer a bargaining agent delays, the less likely the opponent is to continue negotiating (i.e., make a counteroffer). Importantly, we find that these effects are robust and exist even in situations where we expect delay to play a less important role—when delay is short (below the average length of approximately six hours) and in lower-stakes negotiations (for items with lower prices).

We measure the causal effect of delay through an instrumental variables approach, in which we assume that bargaining decisions, such as how much to concede or delay, are correlated for consecutive negotiations (e.g., a buyer who delays more in a negotiation on day t is also more likely to delay in another negotiation on day $t+1$) because of factors that are unrelated to the opponent or the product under negotiation. This assumption allows us to use bargaining decisions from the focal party's previous negotiation with a different opponent for a different item as instruments for the bargaining decisions in the focal negotiation.

The empirical results are consistent with predictions from models of strategic delay (Cramton 1992), in which delay signals a party's payoff. We further show that the bargainer's decision on how much to delay is correlated with proxies of the bargainer's valuation of the product in a way that is consistent with the use of strategic delay. However, we note that although the results are consistent with delay signaling their valuation, we cannot rule out that delay also signals other attributes, such as the bargainer's discount factor or bargaining power in general.

A limitation of this paper is that we do not directly observe whether a bargaining party's response to delay is because they infer that the other party is using delay strategically. This is partly because we only observe the time stamp of when an offer is submitted but not that of when the party that receives the offer actually observes it. In our empirical analysis, we assume that the bargaining party cannot distinguish whether the other party's delay is because of their bargaining power or because of an unrelated event (e.g., spending less time on the internet). We think that this is reasonable because the delay is individual specific as opposed to, say, a platform-wide outage. In the latter case, such a delay would not be informative, and we might see different empirical effects. Therefore, although we observe that delay is empirically consistent with predictions from signaling models, we cannot establish the exact reason that leads delay to have the effects that we observe in practice.

Nevertheless, our results demonstrate that delay can impact the outcomes of negotiations and thus, the efficiency of bargaining interactions. Given that we are able to establish these effects in a setting that has relatively low stakes, we expect that delay plays an even more important role in settings where negotiations have graver consequences, such as wage negotiations. Investigating whether this is the case is a fruitful avenue for future research.

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Endnotes

[1] Hence, this does not correspond to a party's specific perception of delay, which could correspond to the amount of time that their opponent took to respond in excess of their expectation of waiting time.

[2] In our sample, $30 is the bottom quartile of BIN prices.

[3] Notably, this result is often robust to relaxing the complete information assumption. Under one-sided incomplete information, Fudenberg et al. (1985), Gul et al. (1986), and Gul and Sonnenschein (1988) obtained no delay results. In turn, Rubinstein (1985), Perry (1986), and Cho (1990) obtained this result under two-sided incomplete information.

[4] Examples include Evans (1989), Vincent (1989), Cramton (1991), and Deneckere and Liang (2006).

[5] Other examples of papers that obtained delay under two-sided incomplete information are Cramton (1984), Chatterjee and Samuelson (1987, 1988), Ausubel and Deneckere (1992), Watson (1998), Abreu and Gul (2000), Feinberg and Skrzypacz (2005), and Keniston et al. (2024). Importantly, the model from Keniston et al. (2024) aims to rationalize the pervasive empirical finding of "split-the-difference" behavior, which also holds in our data.

[6] It thus generalizes the one-sided incomplete information setting of Admati and Perry (1987).

[7] The data and their associated descriptions can be found in https://www.nber.org/research/data/best-offer-sequential-bargaining.

[8] However, there is evidence that delay can affect parties' perception and satisfaction with the outcomes (Srivastava and Oza 2006).

[9] These policies were true for the period in which the data were collected. In 2017, eBay modified the policies to allow at most five offers in total, and in 2021, eBay modified the policies to have each offer expire after 24 hours.

[10] About 0.7% of all negotiations reach round 6. We report the distribution of the number of rounds per thread in Table D.2 in the Online Appendix.

[11] For example, consider the following sequence; the buyer makes an offer, the seller declines, and then, the buyer makes another offer. The latter offer from the buyer is not considered a counteroffer in this paper.

[12] For a comprehensive list of the variables in these data, see https://www.nber.org/research/data/best-offer-sequential-bargaining.

[13] A more thorough description of *all* offers can be found in Backus et al. (2020).

[14] Seventy-two percent of rejections of the seller's first counteroffer are expired, and 34% of rejections of the buyer's first counteroffers are expired. That is, conditional on declining, sellers actively decline offers more frequently than buyers do.

[15] The other approximately 4% of counteroffers end because the seller sells the product to another buyer before the focal buyer responds.

[16] Parties can autoaccept or autodecline. The counteroffer response times do not include autoresponses.

[17] Tables D.3 and D.4 in the Online Appendix display the estimated coefficients.

[18] One can also consider another version of this DGP in which p_{k2} and w_{k2} are jointly determined. As such, f_{k2}^{p} would include w_{k2}, and f_{k2}^{w} would include p_{k2}. This version of the DGP does not have different implications for our identification strategy.

[19] We relax this assumption in a robustness check in which the instrument is the seller's previous negotiation with a different buyer for a different item, unconditional on the negotiation round. The results of the robustness check are reported in Tables D.8 and D.9 in the Online Appendix.

[20] Each bucket is a one-hour range (e.g., zero to one hour, one to two hours, etc.).

[21] One may be concerned that this instrument violates the monotonicity condition when the concession weight is close to zero or one. As a robustness check, we omit observations where the relationship between the instrument and the endogenous variable is not monotonic, which is when the concession weight of the current offer is below 0.05 or above 0.95 for sellers' counteroffers or above 0.85 for buyers' counteroffers. This removes 2.3% and 6.8% of seller and buyer counteroffers, respectively. Tables D.15 and D.16 in the Online Appendix report the effects on the other party's response for this subsample. These results are similar to our main results.

[22] The dollar amount is derived from the average offer price of $120.71 ($120.71 \times 0.0061 = 0.74$).

[23] The estimates of this regression—the effect of buyer delay on whether the item is sold in the focal thread conditional on the seller countering or declining the buyer's first counteroffer—are reported in Table D.13 in the Online Appendix.

[24] Estimates are reported in panel (a) of Table D.10 and panel (a) of Table D.14 in the Online Appendix.

[25] Estimates are reported in panel (b) of Table D.10 and panel (b) of Table D.14 in the Online Appendix.

[26] This removes an additional 12% of seller counteroffers and 21% of buyer counteroffers.

[27] Estimates are reported in panel (c) of Table D.10 and panel (c) of Table D.14 in the Online Appendix.

[28] The estimates of this robustness check are not reported in the paper but can be produced if requested.

[29] Admati and Perry (1987) considered a setting with one-sided incomplete information.

[30] We thank an anonymous reviewer for suggesting this exercise.

[31] Specifically, "similar" items are those with the same listing title as the focal item that were sold during the time frame of the data.

[32] These include Admati and Perry (1987) and Cramton (1992), for example, as proven by Freyberger and Larsen (2025).

[33] This assumption is also maintained in Cramton (1992). We refer readers to a detailed discussion of this assumption in Freyberger and Larsen (2025).

[34] We refer readers to Backus et al. (2020) for a more in-depth discussion of empirical patterns in this data set that are not fully explained by existing models.

[35] The buyer also switches from accepting to declining when the seller delays longer but to a smaller degree than the likelihood of switching from countering to declining.

[36] Empirically, buyers and sellers seem to respond to competition. Buyers are less likely to accept sellers' counteroffers if there are more new listings in the same product category as the item under negotiation (Table D.19 in the Online Appendix). Similarly, sellers are more likely to counter and less likely to decline buyers' counteroffers if the sellers have more competition: that is, that there are more new listings in the product category (Table D.20 in the Online Appendix).

[37] For both buyers and sellers, the more the party concedes, the more likely the other party is to accept, and the less likely they are to decline.

[38] One might try to attribute it to the buyer assuming that the seller has already sold the item to another buyer. However, this is likely not true in our setting because of eBay's platform design; if the seller completes the transaction with another buyer, all other buyers in active threads for that item are notified immediately.

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