Dynamics of Bargaining

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Extended Abstract

When bargaining, do agents have prepared strategies? For example, does someone selling their car know exactly what offers they will accept and what offers they will reject? If a seller has a prepared strategy, then they should, on average, reject all offers in the same amount of time and accept all offers in the same amount of time. Alternatively, if sellers instead evaluate offers on the spot, they should be more hesitant to reject higher offers or to accept lower offers (Konovalov and Krajbich 2017). Conditional on rejection, sellers should be faster in response to lower offers. Conditional on acceptance, sellers should be slower in response to lower offers. We test these hypotheses in a dataset of bargaining exchanges on eBay to establish whether agents in the market have prepared strategies.

Lab experiments have confirmed that subjects' response times (RT) reveal their strength-of-preference in a variety of domains including risky choice, intertemporal choice, food choice and altruistic decisions (Konovalov & Krajbich 2019). Choices closer to indifference tend to take more time. Moreover, a computational model called the Drift Diffusion Model (DDM) can account for this behavior (Ratcliff and McKoon, 2008, Busemeyer and Townsend, 1993). The core assumption of the model is that decisions are the result of an evidence accumulation process. The model has four key parameters. Changes in these parameters will produces changes in choice probabilities and RT. For instance, one parameter called the decision boundary represents the caution level. Increasing the decision boundaries makes choices more accurate but slower. Another parameter called the drift rate represents the evaluation process. The more positive the drift rate is, in this case the higher the surplus earned, the more likely the offer will be accepted. The larger the absolute value of the drift rate is, the quicker the decisions will be made on average. The drift rate reflects the strength-of-preference – when a subject is close to indifferent, their drift rate is close to zero and so their decision will tend to be slow.

In lab bargaining data, Konovalov & Krajbich (2017) demonstrate that subjects' RTs reveal the difference between their private value and the price offer. However, it is an open question whether these quick decisions by inexperienced students generalize beyond the lab to markets with experienced agents. To this end, we analyze bargaining exchanges from eBay and ask whether RT reflects the gap between sellers' prices and buyers' offers, even when RT is on the order of hours instead of seconds.

We use an online dataset of millions of bargaining exchanges on eBay. On eBay, a seller can post an item for sale, but they can also enable a bargaining feature at no cost. This allows buyers to initiate a bargaining process. Both sellers and buyers can accept, reject, or counter offers. There is a 48-hour deadline to respond to each offer, after which the offer is automatically rejected. Although sellers can set automatic acceptance or rejection thresholds, only 49% do so. We focus our analyses on exchanges without automatic thresholds. We also re-analyze the lab bargaining data from Konovalov & Krajbich (2017).

In the eBay dataset (N = 1,018,858), over most of the offer range ([25%, 100%]), median acceptance times decreased monotonically with offer size, from 2.1 hours down to 1.0 hours. Similarly, over most of the offer range ([0, 65%]), median rejection times increased monotonically with offer size, from 1.4 hours up to 2 hours. Moreover, the point at which

sellers were equally fast at accepting and rejecting offers (50%, RT = 1.3 hours) is close to the sellers' average indifference point (43%). Generalized additive models identify [0.35, 0.70] as the range of offers for which both acceptance and rejection RTs were monotonic in offer size. In this range, offer size had a significantly negative effect on log(RT) for acceptances and a significantly positive effect on log(RT) for rejections.

We next fit the DDM to both datasets. In the eBay dataset, we fit the DDM to all the sellers that have more than 50 acceptances and 50 rejections (N = 527). In the lab experiment we let the drift rate depend on the difference between the buyer's private value and the offer made by the seller, while in the eBay dataset we let it depend on the ratio of the buyer's first offer to the seller's list price as well as the list price. We find that the DDM fits the lab data extremely well, but it misses some aspects of the eBay data. Although the correlation between the data and the model is high and significant for the eBay data, the model slightly overpredicts the fastest RTs, slightly underpredicts the median RTs, and underpredicts the slowest RTs. Unlike in the lab, there can be long delays before sellers on eBay see their offers (e.g., they could be working or asleep). We need to model such delays. To do so, we extend the standard DDM with a non-decision time that depends on the hour of the day when the offer is made and on the difficulty of the decision (since slow decisions are more likely to be interrupted). This model captures the variation in mean RT over the course of the day and provides better fits to the choice and RT data than the standard DDM.

Using the best-fitting model, we correlate the DDM parameters with various measures of seller experience, such as number of bargaining interactions or number of listings, to investigate how experience might affect sellers' bargaining strategies. We find that more experienced sellers have narrower decision boundaries, which indicates that they are less cautious when responding to offers. We also find that more experienced sellers have a drift bias towards accepting offers, which indicates that they evaluate all offers more positively compared to less experienced sellers. We also find that more experienced sellers are more cautious in responding to high priced listings and have a tendency to reject offers on those listings.

In conclusion, using a dataset of millions of eBay bargaining exchanges, we find that sellers' RTs are strongly related to the size of the offers that they receive. They are quick to accept good offers and reject bad offers, and slow to accept bad offers and reject good offers. This field evidence supports laboratory experiments showing that agents' RTs reflect their strength of preference, even in strategic situations. A computational model, the DDM, captures the field bargaining data well, but only with a more complex model of non-decision time. The modeling confirms that the quality of the offer affects the drift rate and that sellers with more experience still evaluate offers on the spot, though they do so more quickly and more positively than less experienced sellers.

References

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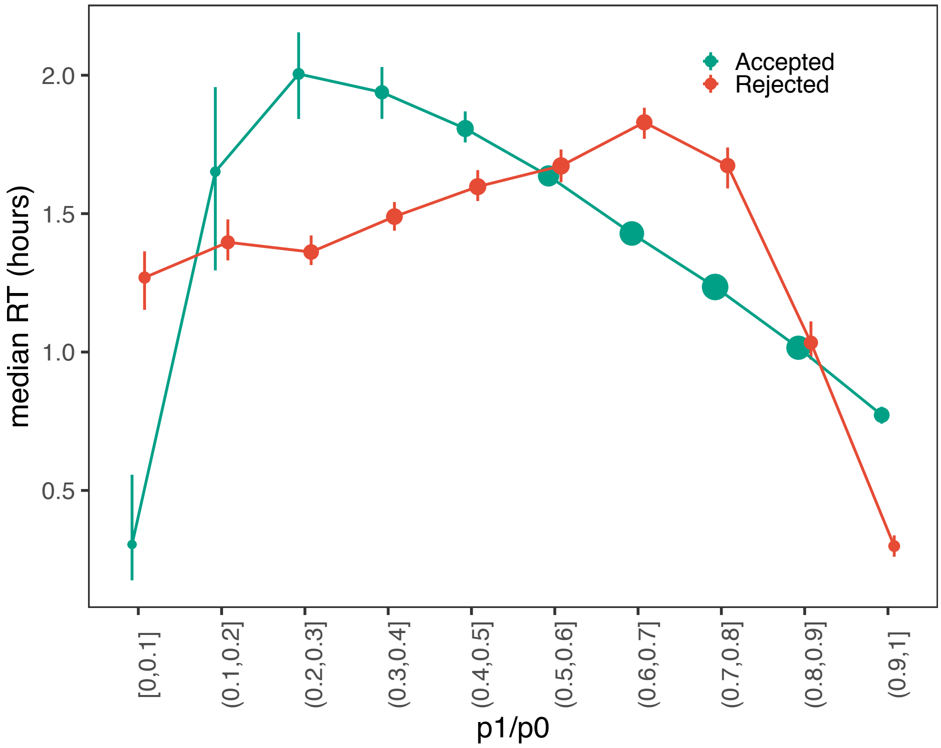

Figure 1. Sellers' median RT (in hours) as a function of buyers' initial offers (p1) (as a fraction of the sellers' list prices (p0)), conditional on the seller accepting or rejecting the offers. The size of the dots indicates the relative amount of data in that bin, across both curves, and the bars represent bootstrapped 95% confidence intervals.