Replication Exercise of Decision Times Reveal Private Information in Strategic Settings: Evidence from Bargaining Experiments

A Replication study of Konovalov and Krajbich (The Economic Journal, November 2023)

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In the 2023 article Decision Times Reveal Private Information in Strategic Settings: Evidence from Bargaining Experiments by Konovalov & Krajbich (2023), researchers examine how people's response times in two-stage bargaining experiments can reveal their preferences (Konovalov & Krajbich, 2023). The study finds that faster rejections by buyers correspond to smaller foregone surpluses, enabling sellers to infer buyers' values from response times. This creates an incentive for buyers to manipulate their response times strategically. The study identifies conditions where subjects exhibit and do not exhibit such strategic behavior, providing initial insights into the use of response time as a strategic variable. This replication reproduces the results and concurs with the original results in terms of the original laboratory data, while reexamining the theoretical and empirical robustness.

Introduction

Response time, the time taken by an agent in sequential bargaining scenarios to make a decision, can provide insights into the decision makers' values and beliefs. This study draws lessons from experimental economics, classic game theory, and mathematical psychology to develop insights on the impact of response time (RT) on sequential bargaining. Theoretically, RTs are viewed as the stochastic outputs of a noisy evidence accumulation process. This choice process is represented by a Brownian motion influenced by both internal (endogenous) stopping rules of decision makers and external (exogenous) evidence. Stronger evidence used towards this process (or larger quantity) leads to shorter response time, indicating a higher strength of preference. RTs could help address problems of asymmetric information, particularly in bargaining scenarios. Laboratory and field evidence suggests that RTs are informative in strategic interactions (Backus et al., 2020; Krajbich et al., 2012). However, strategic use of RTs depends on agents' awareness and attention to this information. The authors of the original article proposed and confirmed that response time reflects strength of preference in strategic situations, but inexperienced agents may not fully utilize or understand their significance. We review the main theoretical foundation drawn from Fudenberg et al.'s application of Drift Diffusion Model (DDM) in sequential bargaining (Fudenberg et al., 2018) and Sobel and Takahashi's model for multistage bargaining (Sobel & Takahashi, 1983). Applying nonparametric techniques for testing model specification, we challenge the statistical significance of relationship established in (Konovalov & Krajbich, 2023).

Experiment Overview

A review of the linkage between the theoretical framework, experimental design, and empirical results is provided as the study is multi-layered conceptually. The study comprises two experiments: the "Live" experiment and the "Explicit-RT" experiment. In the Live experiment, subjects engaged in bargaining tasks where buyers' response times (RTs) were either hidden or visible to sellers. Consistent with Coasian dynamics predictions, buyers accepted the first offer more slowly as their surplus increased. Compared to Hidden treatment, buyers' responses were faster when RT was visible. Subsequently, subjects assumed the role of sellers and attempted to predict buyers' values based on previous bargaining interactions in the selling task. In the Explicit-RT experiment, subjects only bargained in conditions where RTs were hidden and later engaged in a buying task where they had to select between different bargaining situations based on observed values, initial price offers, and RTs. A significantly positive relationship is established between the sellers' second round offers when comparing Hidden and Visible selling, indicating that sellers in real bargaining scenarios' price discriminates as hypothesized. In the buying task where offers are explicitly compared with RT, the researchers found that buyers preferred shorter RT with rejections, indicating that buyers in the experiment understood the impact of RT and were able to manipulate their RTs as (false) signals for buyer that their true value might be low. Additionally, a survey was conducted to assess individuals' attention to RTs in bargaining scenarios outside the laboratory setting.

Theoretical Predictions and Focused Literature

In this section, we review key sources of the study for a comprehensive understanding of the underling theoretical frameworks of the hypotheses.

In Fudenberg et al., the previously derived model of the Drift Diffusion Model (DDM) is applied in sequential bargaining. The drift diffusion model serves as a foundational framework for understanding the decision-making processes in multistage bargaining. It offers a computational account of how individuals accumulate noisy evidence over time. In the baseline RT predictions, the process begins with a buyer observing a good and its initial price simultaneously at time $t = 0$. The buyer then gradually accumulates evidence about her value for the good and the price over time. This evidence accumulation follows a drift-diffusion process denoted as $Z_t = \mu_t + B_t$, where B_t is standard Brownian motion and μ represents the rate of evidence accumulation, known as the drift rate. The accumulated evidence continues until it crosses a boundary b_t, triggering the buyer to either accept or reject the offer. The reaction time (RT) is defined as the time at which $|Z_t|$ reaches b_t or $-b_t$, depending on the action taken. The distribution of RT depends on the endogenous boundary b_t and the exogenous drift rate μ, where narrower boundaries and higher drift rates result in shorter RTs. The drift rate μ is assumed to be strictly increasing in the buyer's true value and strictly decreasing in the price, indicating that higher values lead to a higher likelihood of acceptance, while higher prices lead to a lower likelihood of acceptance. As a standard assumption for a simple drift diffusion process, we assume that b_t is constant over time[1]. Further, as proven in Theorem 1 of Fudenberg et all., using the DDM representation of an agent's choice process P, we infer that P is constant in our experiment (Fudenberg et al., 2018). Hence, the exogenous rate of evidence accumulation is the only variable in our application of DDM.

We now turn to game theoretical literature applied on sequential bargaining with incomplete information. The study derives perfect Bayesian equilibria building upon Coasian dynamics. In the simple two-stage sequential bargaining game, sellers are predicted to price-discriminate with information about buyers' true value, specifically, as it is indicated by RT (Fudenberg & Tirole, 1991). The generalization of this model suggests that, however, increasing uncertainty hurt the seller and bargainers typically preferred to bargain against an opponent with high costs of waiting (Fudenberg et al., 2018). More importantly, if a buyer is indifferent between waiting and accepting the first offer, then she will strictly prefer to take the offer in the first period if and only if her true value is larger than the no-commitment equilibrium price (Sobel & Takahashi, 1983). This was not exhibited in the experiment data. In the Extensions section, we will address the implications of this contradiction.

Conditional distribution of RT is proportional to their rate of evidence accumulation. Given the considerations above, we predict the same as Konovalov and Krajbich that when buyers' response times are concealed, their rejection response times increase with the value of the item and decrease with the price offered, while acceptance response times decrease with the item's value and increase with the price. If sellers have access to buyers' response times unbeknownst to the buyers, they tend to offer lower second prices to buyers with faster response times; similarly, if buyers can manipulate their response times without the sellers' awareness, they tend to reject with faster response times to signal a lower value to the seller.

We provide the main regression tables from the Konovalov and Krajbich's code here.

1 See Konovalov and Krajbich's Appendix E for further explanation about this assumption of boundary on evidence accumulation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	1.408^{***}	1.823^{***}	1.396^{***}	1.002^{***}	1.553^{***}	1.277^{***}	1.435^{***}	1.575^{***}	1.388^{***}
	(0.121)	(0.116)	(0.147)	(0.106)	(0.091)	(0.098)	(0.072)	(0.101)	(0.087)
value	0.257	-0.045	0.371	0.522^{*}	0.112	0.432^{*}	0.277^{*}	0.749^{***}	-0.032
	(0.226)	(0.196)	(0.262)	(0.238)	(0.155)	(0.172)	(0.121)	(0.202)	(0.128)
accept1	0.394	0.163	0.241	-0.054	0.303	0.145	0.247^{*}	0.128	2.770^{*}
	(0.239)	(0.211)	(0.213)	(0.187)	(0.157)	(0.164)	(0.102)	(0.121)	(1.335)
price1	-0.134	-0.324	-0.582	-0.445	-0.193	-0.487^{*}	-0.295^{*}	-1.259^{***}	-0.058
	(0.222)	(0.235)	(0.306)	(0.289)	(0.159)	(0.214)	(0.141)	(0.277)	(0.158)
Period	-0.015^{***}	-0.022^{***}	-0.005	-0.001	-0.019^{***}	-0.003	-0.011^{***}	-0.007^{**}	-0.014^{***}
	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
easy	-0.106	-0.188^{*}	-0.134	-0.037	-0.144^{*}	-0.094	-0.116^{**}		
	(0.094)	(0.077)	(0.119)	(0.091)	(0.061)	(0.073)	(0.045)		
value:accept1	-0.756^{*}	-0.465	-1.134^{***}	-0.355	-0.622^{**}	-0.823^{**}	-0.743^{***}	-1.199^{***}	3.054^{**}
	(0.300)	(0.240)	(0.332)	(0.346)	(0.190)	(0.256)	(0.138)	(0.217)	(1.117)
accept1:price1	0.284	0.540	1.259^{**}	0.624	0.376	0.941^{*}	0.642^{*}	1.565^{***}	-6.571^{*}
	(0.487)	(0.428)	(0.441)	(0.490)	(0.327)	(0.379)	(0.250)	(0.353)	(2.894)
visible					0.093	-0.155^{*}	0.090	-0.022	-0.029
					(0.060)	(0.076)	(0.059)	(0.039)	(0.041)
part							-0.082	-0.184^{***}	-0.233^{***}
							(0.059)	(0.040)	(0.041)
visible:part							-0.246^{*}		
							(0.121)		
R^2	0.083	0.161	0.142	0.083	0.123	0.125	0.147	0.087	0.133
Num. obs.	418	476	476	419	894	895	1789	1029	760

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Statistical models

Figure 1: Table B2. Buyer's RT in the Live experiment, bargaining task. OLS fits of log(RT) in seconds.

	(1)	(2)	(3)	(4)
(Intercept)	1.59^{***}	1.77^{***}	1.79^{***}	1.47^{***}
	(0.08)	(0.08)	(0.11)	(0.11)
value	0.64^{***}	0.21^{*}	0.68^{**}	-0.05
	(0.09)	(0.10)	(0.23)	(0.12)
accept1	0.21	0.05	0.01	0.86^{**}
	(0.16)	(0.16)	(0.18)	(0.26)
price1	-0.52^{***}	-0.19	-0.96^{**}	0.07
	(0.14)	(0.14)	(0.35)	(0.16)
Period	-0.02^{***}	-0.02^{***}	-0.02^{***}	-0.03^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
value:accept1	-1.22^{***}	-0.91^{***}	-1.38^{***}	5.40^{***}
	(0.20)	(0.20)	(0.30)	(0.80)
accept1:price1	1.47^{***}	1.31^{***}	2.03^{***}	-4.59^{***}
	(0.29)	(0.28)	(0.50)	(0.83)
easy		-0.27^{***}		
		(0.05)		
R^2	0.20	0.23	0.14	0.20
Num. obs.	654	654	368	286

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Statistical models

Figure 2: Table B3 Explicit-RT experiment, bargaining task. OLS fits of log(RT) in seconds.

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	11.01	1.95	-3.72	5.69	8.52	4.97
	(7.17)	(3.66)	(5.13)	(6.37)	(5.95)	(4.29)
rtb	0.12	-0.51^{*}	-0.43	1.26^{**}	0.05	-0.54
	(0.33)	(0.26)	(0.32)	(0.45)	(0.33)	(0.31)
price1	0.37^{*}	0.65^{***}	0.81^{***}	0.48^{***}	0.46^{***}	0.63^{***}
	(0.16)	(0.07)	(0.12)	(0.13)	(0.12)	(0.10)
Period	0.28	-0.02	0.14	0.06	0.13	0.06
	(0.20)	(0.11)	(0.13)	(0.09)	(0.12)	(0.08)
visible					0.16	-6.63^{*}
					(2.84)	(3.20)
rtb:visible					-0.50	1.84^{***}
					(0.43)	(0.53)
R^2	0.21	0.40	0.50	0.27	0.29	0.38
Num. obs.	285	329	325	326	614	651

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Statistical models

Figure 3: Table B4 Second-stage offers in the Live experiment, bargaining task. OLS fits of new offers, conditional on the first offer rejection.

	(1)	(2)	(3)	(4)
(Intercept)	11.154^{***}	9.067^{***}	10.368^{***}	11.249^{***}
	(2.374)	(2.662)	(3.115)	(3.059)
rt	0.239	-0.316	0.954^{**}	0.543
	(0.323)	(0.260)	(0.291)	(0.327)
price1	0.435^{***}	0.508^{***}	0.423^{***}	0.482^{***}
	(0.031)	(0.048)	(0.058)	(0.048)
Period	0.002	0.278^{**}	0.123	-0.009
	(0.101)	(0.085)	(0.090)	(0.112)
R^2	0.270	0.209	0.135	0.180
Num. obs.	816	904	979	825

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Statistical models

Figure 4: Table B5. Live experiment, selling task. OLS fits of new offers.

	(1)	(2)	(3)	(4)	(5)
(Intercept)	20.66^{***}	-3.76^{*}	-5.44^{**}	-5.77^{**}	-4.82^{*}
	(1.35)	(1.58)	(1.84)	(1.90)	(2.09)
rt	2.39^{***}	2.49^{***}	2.49^{***}	2.49^{***}	2.26^{***}
	(0.26)	(0.23)	(0.23)	(0.23)	(0.35)
price1		0.52^{***}	0.53^{***}	0.53^{***}	0.53^{***}
		(0.03)	(0.03)	(0.03)	(0.03)
Period			0.15^{*}	0.15^{*}	0.15^{*}
			(0.06)	(0.06)	(0.06)
type				0.64	-1.34
				(1.26)	(2.42)
rt:type					0.45
					(0.46)
R^2	0.13	0.43	0.43	0.43	0.43
Num. obs.	1320	1320	1320	1320	1320

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Statistical models

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Figure 5: Table B6. Explicit-RT experiment, selling task. OLS fits of new offers.

Extensions

The article provides a thoroughly tractable confirmation on the conventional knowledge and game theoretical framework of understanding sequential bargaining. This is the first known literature to confirm longstanding theoretical predictions about multistage sequential bargaining with evidence from the field of psychology, using real data in a controlled environment. As a replication study, we seek to refine areas of existing work that deserve further inspection.

To provide a more robust statistical foundation for the results, we move forward with testing with bootstrapping methods. The authors' initial results were achieved exactly using original data and code[2]. It is noticeable that the statistical significance of the original results varies, with some using confidence level 10% and some satisfactory at 5%. It seems that the inference process in the original paper is worth reconsidering. Therefore, this exercise moves forward with a robustness check that examines the specification of estimators used (linear regression models via OLS). We use a consistent test put forward by described in Hsiao, Li, and Racine (Hsiao et al., 2007) and implemented with the `np` package (Hayfield & Racine, n.d.; Jeffrey Racine, 2023).

All statistical relationships in the results are established using linear parametric regression. Specifically, for example, in Result 3, to confirm the hypothesis of price discrimination on the sellers' part, the authors observed that the majority of subjects made higher offers to buyers with longer RTs, controlling for the first offer. This is concluded by regressing second offer prices over 20 periods at subject level[3]. Considering the scope of work described in the article, OLS is a reasonable choice for hypothesis testing. However, for a sampling method like the one conducted in this study, issues such as violation of normality and overfitting can threaten the validity of results. Replication results for the original Result 3 suggest that a large portion of the parametric regression for the data is not correctly specified[4]. Therefore, we conclude that a positive linear parametric relationship between RT is only weakly established and requires more data and more experimentation with regression techniques. A more comprehensive description of a potentially non-parametric relationship can be established with significance to further study how RT might influence offers. As suggested, we argue that the positive relationship previously established between response time and second price

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2 Replication Package is available at https://zenodo.org/records/8170197

3 In the original replication package, this method can be found at line 25-40 in `main.R`.

4 This is computed with `npcmstest` using the wild bootstrapping method (due to the small sample size. With only 48/77 subjects exhibiting that the linear regression is correctly specified. See `appendix.R` for the implementation.

(controlling for first price) in the Explicit–RT experiment is not significant, and we cannot conclude that the sellers understood the relationship between RT and buyers' values and used that information to make better offers using existing data and methods.

	(1)	(2)	(3)	(4)
(Intercept)	-0.006	-0.178	-0.178	-0.184
	(0.070)	(0.157)	(0.155)	(0.157)
valuedif	0.129^{***}	0.129^{***}	0.129^{***}	0.129^{***}
	(0.018)	(0.018)	(0.018)	(0.018)
rtdif	-0.080^{*}	-0.080^{*}	-0.080^{*}	-0.080^{*}
	(0.038)	(0.039)	(0.040)	(0.038)
pricedif	-0.062^{***}	-0.062^{***}	-0.062^{***}	-0.062^{***}
	(0.010)	(0.010)	(0.010)	(0.010)
Period		0.011	0.011	0.011
		(0.009)	(0.009)	(0.009)
pricedif:rtdif			-0.000	
			(0.002)	
valuedif:rtdif				0.001
				(0.002)
AIC	1121.975	1122.381	1124.379	1124.027
BIC	1144.338	1150.335	1157.924	1157.572
Log Likelihood	-556.987	-556.191	-556.189	-556.014
Deviance	1113.975	1112.381	1112.379	1112.027
Num. obs.	1980	1980	1980	1980

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Statistical models

Figure 6: Konovalov and Krajbach (2023)'s regression results

Replication results Table: Jn statistics and P-values of consistent test for correct specification of linear models.

	Jn statistics	p-value
Model (1)	92.3404160482609	0
Model (2)	92.1887906960434	0
Model (3)	109.209160065463	0
Model (4)	1.50880486766242	0.0025062656641604

Figure 7: Robustness check. The null hypothesis for this test is that the linear parametric model is correctly specified. As the p-values suggest, none of the models is consistently correct, which contradicts Konovalov and Krajbich's Result 6-7.[5]

[5] See appendix.R for our code on this robustness check. Note that npcmstest() may take a long time to compute depending on computing resources available.

We observe that the model specifications applied to deduce buyers' preference for "a higher value, a lower first offer, and a shorter RT" are not consistent. Therefore, we point out that the original paper's conclusion that the subjects understood the strategic advantage of leveraging RT is only loosely found in this experiment.

We move on to investigate the effects of RT on the efficiency of bargaining, as represented by total surplus using the Sobel and Takahashi model. Following the model established by Konovalov and Krajbich, we deduce expected total surplus of the baseline model to be:

$$T = \frac{(12 - 8\delta - \delta^2)(4 - 3\delta)^{-1}}{8}$$

$$T = 0.992$$

Sobel and Takahashi point out that increasing δ (discount factor) would lead to (a) direct effect of increasing surplus by reducing bargaining cost; and (b) indirect effect of decreasing surplus by increasing the price of next round p_2. In an infinite horizon extension, we can remodel Konovalov and Krajbich's suggested cost of slow response c and consider a non-constant discount factor. As Konovalov and Krajbich confirmed, subjects exhibited faster response when cost is high, thus, confirming that Theorem of Sobel and Takahashi is realistic. To observe that effect of RT on total surplus in this experiment, we build upon Result 7 of Konovalov and Krajbich and the differences in total surplus.

Conclusion

In this replication exercise, we are able to confirm that Konovalov and Krajbich 2023's empirical results confirm its theoretical hypotheses. However, a more comprehensive econometric testing for consistent model specification suggests that the relationship between response time and the awareness of leveraging it to optimize profit is not sufficiently established. This was found by regressing offer data on RT collected in part of the experiment where RTs are presented explicitly to subjects. Although in sequential bargaining situations, these are well-known conventional knowledge, this experiment is not able to confirm that this occurs in the real world. In other words, we cannot conclude that the subjects make price decisions optimally by utilizing RT as information about their bargaining opponent. To further investigate this subject, researchers might consider collecting larger amounts of bargaining data in the field or conducting extensions of the existing experiment for meaningfully larger samples to work with. As well, econometricians might consider non-parametric models as an alternative for linear parametric models used throughout the original paper.

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