Should one really think twice before running? An experimental investigation on decision making and response time

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Abstract

This paper focuses on the connection between response time and making the right decision in context of bankruns. Using experimental dataset it concludes via logit, fixed effect logit, random effect logit models and survival analysis that if the respondents have dominant strategy, it is worth spending time with thinking.

Keywords: bankrun, response time, survival analysis

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1 INTRODUCTION

In their paper studying experimental data on bank runs and cognitive abilities Kiss et al. [4] state "Think twice before running!". After building a game theoretical framework the authors conducted a computer-based experiment to examine what are the hidden factors and motives of bank runs. They conclude that in case of strategic uncertainty the participants' cognitive abilities matter in choosing the right decision; however, if uncertainty is absent, cognitive abilities do not have significant effect on the participants' choice. In this aspect their contribution is indisputable; nevertheless, they did not prove their question: is it actually worth to spend time with thinking?

This paper addresses this question. With the usage of participants' response time it investigates whether thinking (response) time is beneficial or one should trust her instinct and decide immediately. The intuition might be clear: thinking drives people to the right decision. However growing literature suggests that this question is not that simple. For example according several computer-based games, Rubinstein [7] finds that there are cases (games, or positions in a certain game) when the contemplative decisions do worse than instinctive decisions. To answer the question this paper will use logit, fixed and random effect panel methods on the experimental data and conclude that in this game the response time has a positive effect on choosing the right decision, where there is a dominant strategy of respondents.

This paper is structured as follows: the next section summarizes the theoretical and empirical framework, namely, the game theoretical and experimental background. Section 3 describes the data, and Section 4 and 5 introducing the econometric models and stating their main assumptions, limitations and results. Finally, Section 6 makes conclusion.

2 THEORETICAL AND EMPIRICAL FRAMEWORK

While the early research on modeling bank runs focused on simultaneous decision making (see Diamond and Dybvig [2]), further developments were made in the direction of sequential ones. [1] The motivation is clear: in case of real bank runs people often see others' action (e.g. huge queues before the banks or ATMs), and they make their decision according to them (to withdraw her money or keep it in the bank).

With the same logic Kiss et al. [4] makes simple sequential bank run game with 3 depositors. The depositor on the first place decides at the beginning whether she withdraws or keeps her money in the bank. After she the second depositor chooses; and after the second the third one. To make the setting more complex the authors introduces eight different information settings. In each setting the depositors can observe or can be observed in different ways. For example in one setting the second can observe the first and the third can observe both the first and second (it is a complete information setting), in an other setting third can observe again both, but second cannot the first.

Because of the lack of information in several information settings, uncertainty can be introduced. In an uncertain case the depositor cannot observe at least one subsequent depositor's action. According to Kiss et al.'s [4] results, this uncertainty has a significant effect on choosing the correct decision. Despite the risk, the authors claim and shows that the depositors on the third place have the dominant strategy to keep their money in the bank (see p.4. for the whole argument), therefore they only focus with their analysis on the depositors on the third place.

[1] Kiss et al. [5] examines in an experimental setting the effect of social networks related to bankruns. Schotter and Yorulmazer [8] shows that information about the quality of the bank and even a minimalist deposit insurance can mitigate the risk and damage of bankruns. Furthermore Campioni et al. [1] introduces financial literacy and concludes that if the agents know how the others are financially educated, in case of bigger banks the runs are avoidable. However these studies are examining different questions, the experimental, sequential methodology is similar among them.

To obtain data, the authors conducted a computer-based experiment with 60 randomly assigned participants (Economics and Business students) in two session (30 in each). They used on average 15 euros as money incentive, which was given to a randomly picked participant per session. Note, that out of the three depositors one was always a computer-simulated actor, who always withdrew her money.

In consonance with the precedings this paper states the hypothesis as follows:

Hypothesis 1. *"The thinking (response) time has a significant positive effect on decision if depositor has a dominant strategy* [2] *(i.e. she is at position 3)."*

[2] Note, one need here to have dominant strategy to be sure, which decision (keep or withdraw) is the right choice. The same question can be asked for the second position, but the right choice is relatively unclear there. Therefore that case is out of the scope of this text.

3 DATA

All the data is used in the study is computer-based. The main dependent variable is *choice*, a dummy variable 0 if the depositor keeps her money in the bank, 1 if she withdraws. The main explanatory variable is *response*, which is in seconds and means how much time the participant spent with her decision. And other controls are: $struncert2$ (1 in case of uncertainty, 0 if it is absent), CRT_sum (measuring cognitive abilities with Cognitive Reflection Test on a 0-3 scale, where 0 is the worst and 3 is the best) $postion$, (position) and $gender$ (0 if male, 1 if female).

One can see the relevant variables' descriptive statistics in Table 1 for the decisions made in the first and second period. The sample is balanced as far as the gender distribution is concerned. In most cases the participants kept their money in the bank, and spent on average 19.3 seconds with decision making, however latters' standard deviation seems relatively high.

Table 1: The descriptive statistics at position 1 and 2

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
choice	588	0.361	0.481	0	1
gender	588	0.495	0.500	0	1
riskav	588	1.718	1.079	0	4
crt_sum	588	0.551	0.962	0	3
response	588	18.73	13.86	1	92
struncert2	588	0.906	0.291	0	1
Number of subject	50	50	50	50	50

In the third position the participants almost had the same circumstances (see Table 2. for the descriptives), however their dominant strategy (namely, keeping their money in the banks) can be observed: their withdrawal rate is half of the previous ones'. Moreover, their average respond time became higher, but it does not seem as a significant difference.

Table 2: The descriptive statistics at position 3

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
choice	312	0.106	0.308	0	1
gender	312	0.510	0.501	0	1
riskav	312	1.667	1.054	0	4
crt_sum	312	0.596	0.994	0	3
response	312	20.40	15.43	2	96
struncert2	312	0.561	0.497	0	1
Number of subject	50	50	50	50	50

As far as the distribution of response time at the third position is concerned, moderate differences can be seen between withdraws and waits. Looking at the histograms (Figure 1 and Figure 2) and not considering the outliers one can argue that response time of waits has longer right-tail. Seemingly, this means that there *might be* positive relationship between response time and choosing the right alternative. But to clarify this question logit, fixed and random effect logit models are used in the next section.

Figure 1: The distribution of third pos. response time if participants withdraw

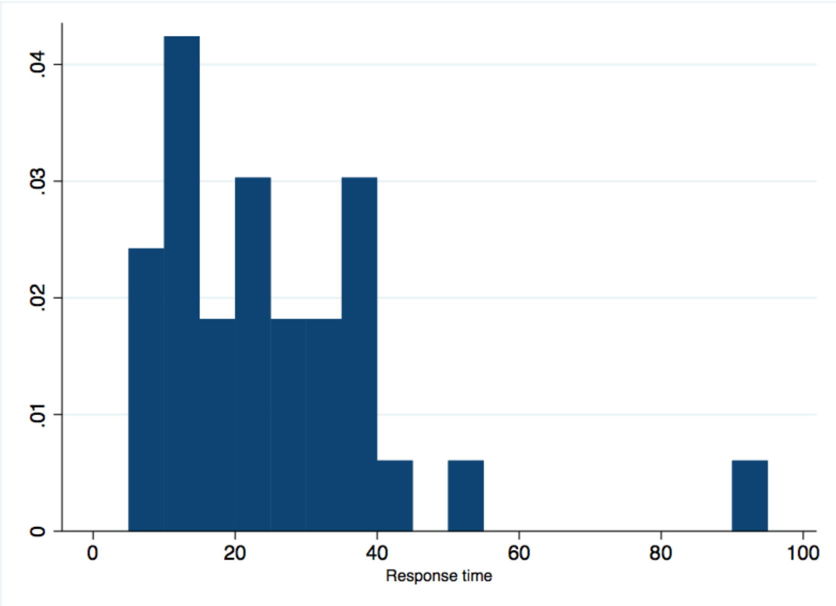
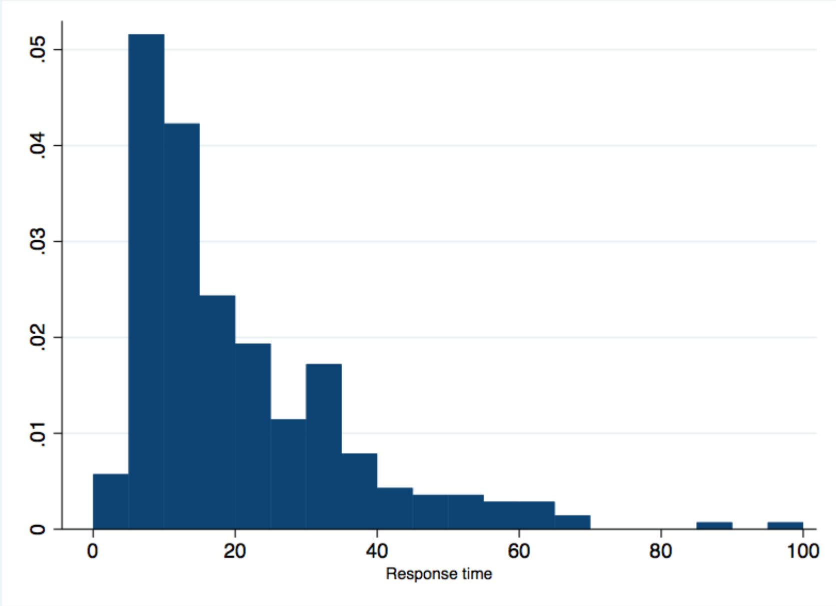


Figure 2: The distribution of third pos. response time if participants wait



4 LOGIT, FIXED AND RANDOM EFFECT LOGIT MODELS

Since the outcome variable is binary (0 if the participant keeps her money in the bank, and 1 if she withdraws), this paper will consider logit models. The first model in Table 3 is a simple one: only the response time's interaction with positions and uncertainty dummy occurs. To obtain an unbiased estimator of response time, adding available individual characteristics (risk-aversion, cognitive abilities, gender) into the model is crucial and considered in Model 3. However one should not really concerned that third model's estimator is unbiased, since the main explanatory variable can be still correlated with the error term causing serious endogeneity.

To handle this issue, fixed effect methods in panel data can be a right choice[3], however one should make basic assumptions here.

Assumption 1. *The endogeneity is present because of one cannot control on all individual characteristics, that vary across participants but not across time during the game.*

Assumption 2. *After time demeaning response time does not correlates with the error term. In this case this means that the dispersion of individuals' response time is due to randomness.*

Assumption 3. *Response time is equivalent to thinking time. It is a homogeneous time, that is totally spend with thinking.*

Holding these assumptions one can use fixed effect estimation on the dataset (Model 3 in Table 3).

Table 3 contains the regression results [4]. The outcome variable is the participants' choices: keep their money in the bank (zero), or withdraw (one) it. The main explanatory variable is response time interacted with the position dummies. In this setting the benchmark is the first position. Our main

[3] Since the data consists of observation of 60 individuals in 15 periods, it is a fully balanced panel structure.
[4] All the project's scripts are available at the author's Github profile: https://github.com/bencear/

interest is whether response time in the third position has a significant effect on decision making or not. In order to answer this question logit models are used. In the Model 1 just the main explanatory variables are added, however using control variables in the Model 2 one can avoid Omitted Variable Bias. In both cases the third position's response time is significantly negative which means, in that case the response time has a positive effect on choice [5]

Model 3 contains the fixed effect estimations. As earlier mentioned the main explanatory variables can correlate with the error term, even if one used wide range of controls. To handle this issue fixed effect method is used on the dataset [6]. In this case response time in the third place also has a negative effect, but lower magnitude.

In Table 3 the random effect model is also shown. Using Hausman-test one can conclude that there is no significant difference between the fixed effect and random effect model (since chi(5) = 4.77, can not reject Hausmann's null-hypothesis).

To sum up, according to these models, one cannot reject this papers main hypothesis. However, since the significance of the uncertainty variable further investigations should be made toward the connection of response time and uncertainty.

With splitting the sample into two parts (certain and uncertain) at position 3, further estimations can be made with logit, fixed effect logit, random effect logit models. Note here, that in this reduced case the number of fixed effect observation declined, however for illustration purposes they are shown in Table 4 and 5.

[5] Recall, the dominant strategy here is to keep the money in bank, so ceteris paribus if response time increases the agent is more likely to *keep* her money in the bank. So thinking more actually drives to better decisions

[6] According to Wooldridge [3] using fixed effect method for a relatively longer time period one should be concerned that serial correlation is not present. For this case using Wooldridge's test one cannot reject its null-hypothesis: the absence of serial correlation (p-value: 0.4061); therefore using clustered errors is not a necessary

Table 3: The estimated logit-models

VARIABLES	(1) logit model	(2) logit w/controls	(3) fixed effect	(4) random effect
response	0.00914	0.00694	0.0188*	0.0178*
	(0.00830)	(0.00862)	(0.0111)	(0.0107)
response_pos2	0.0163**	0.0183**	0.0121	0.0147
	(0.00774)	(0.00793)	(0.00917)	(0.00910)
response_pos3	-0.0252***	-0.0242**	-0.0391***	-0.0373***
	(0.00947)	(0.00963)	(0.0113)	(0.0112)
struncert2	2.313***	2.373***	2.859***	2.726***
	(0.400)	(0.404)	(0.503)	(0.452)
1.crt_sum		0.783***		1.155*
		(0.259)		(0.666)
2.crt_sum		-1.020***		-1.246
		(0.384)		(0.793)
3.crt_sum		0.790***		1.109
		(0.303)		(0.749)
riskav		0.00614		-0.0120
		(0.0863)		(0.207)
gender		0.223		0.347
		(0.191)		(0.467)
period	0.00121	-0.00218	0.00236	0.00184
	(0.0190)	(0.0194)	(0.0221)	(0.0221)
/lnsig2u				0.535*
				(0.294)
Constant	-3.202***	-3.431***		-4.247***
	(0.436)	(0.491)		(0.754)
Observations	900	900	765	900
Number of subject			51	60

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: The estimated models (with uncertainty)

	(1)	(2)	(3)
VARIABLES	logit	fixed effect	random effect
response3	-0.0144	-0.0465	-0.0316
	(0.0155)	(0.0285)	(0.0238)
1.crt_sum	-0.941		-1.144
	(0.864)		(1.427)
2.crt_sum	-2.077*		-2.617
	(1.090)		(1.644)
30.crt_sum	-		-
riskav	-0.198		-0.316
	(0.230)		(0.411)
gender	-0.238		-0.290
	(0.513)		(0.959)
period	-0.156***	-0.260***	-0.232***
	(0.0568)	(0.0956)	(0.0829)
/lnsig2u			1.094
			(0.702)
Constant	0.584		0.946
	(0.840)		(1.387)
Observations	162	61	162
Number of subject		14	50

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

With uncertainty all these models lose their signifcance, the inner experience variable (period) remains significantly negative, which shows that, ceteris paribus as the player become more experienced in this setting (i.e. played more games), they tend to decide better (i.e. keep their money in the bank).

In case of total certainty these model specifications also lose their explanatory power. The key difference between the former and latter models is the number of observation. In the former case with the dummy interaction (response time with position dummies) one could maintain the full observation number. However in latter case the observation number drops down, so as the significance.

Table 5: The estimated models (without uncertainty)

VARIABLES	(1) logit	(2) fixed effect	(3) random effect
response3	0.0619**	0.135	0.129
	(0.0277)	(0.142)	(0.0859)
period	0.118	0.118	0.191
	(0.131)	(0.212)	(0.240)
1.crt_sum	6.060***		15.21
	(2.298)		(9.959)
2.crt_sum	4.870**		12.28
	(2.064)		(9.038)
30.crt_sum	-		-
riskav	0.707		1.980
	(0.838)		(2.622)
gender	4.849**		12.35
	(2.131)		(8.994)
o.period			-
/lnsig2u			2.862**
			(1.447)
Constant	-12.38***		-30.31
	(3.843)		(18.67)
Observations	124	8	124
Number of subject		2	50

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This section showed that response time at the third position has significant effect on decision making: participants with greater response time chose better (estimators of Table 3). However the connection between uncertainty remained unclear (estimators of Table 4 and 5). In order to map the relation of response time and uncertainty survival analysis will be used.

5 SURVIVAL ANALYSIS

In order to examine the main drivers behind response time survival analysis will be used. With this methodology one can examine data where the main dependent variable is response or waiting time and there are explanatory variables, whose effect one would like to control on (Rodriquez [6]). This method is widely used in biology, epidemiology, medical science, sociology where the main question is basically time-related (e.g. time of death, marriage, divorce, infection, etc.)

In this setting the main time variable is response time, (only third positions' will be considered). And there are two events: the participant waits or withdraws [7]. The explanatory variables are the same that has been used previously: gender, cognitive abilities, risk aversion, uncertainty, number of period. Furthermore in this section both semi-parametric (Cox regression model) and non-parametric (Kaplan-Meier and hazard function estimation) methods will be used [8].

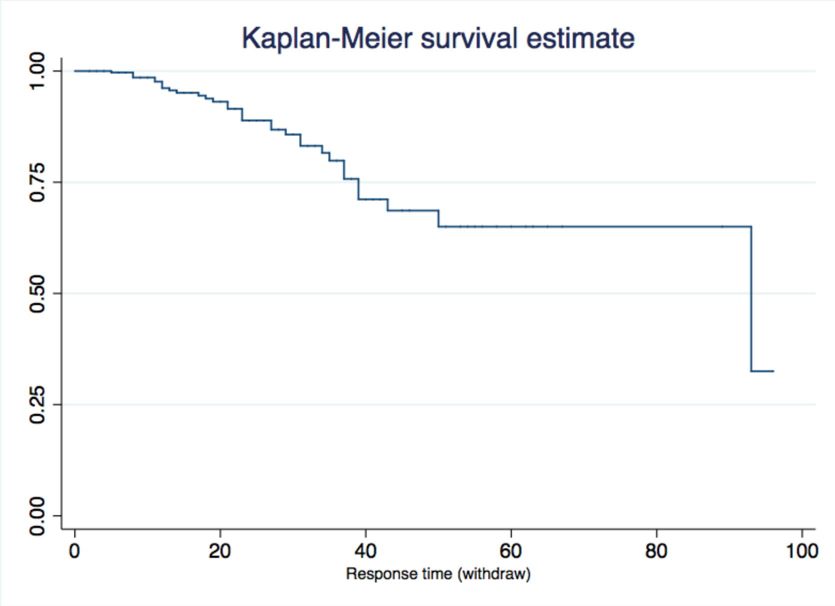
Survival and hazard functions are crucial in survival analysis. Survival function shows the probability of the event does not happen yet, hazard function shows the probability the event occurs if it has not yet.

On Figure 3 and Figure 4 one can see the survival functions of the two segments with Kaplan-Meier (or product limit estimator). The basic tendency looks clear. The participants make the wrong decision (Figure 3) at the beginning of their response (between 15s and 25s).

[7] Note here, this separation is needed, because in the experimental setting the participants had to choose between waiting and withdrawing the money. Therefore this analysis needs two separated discussions: one for waiting, one for withdrawing

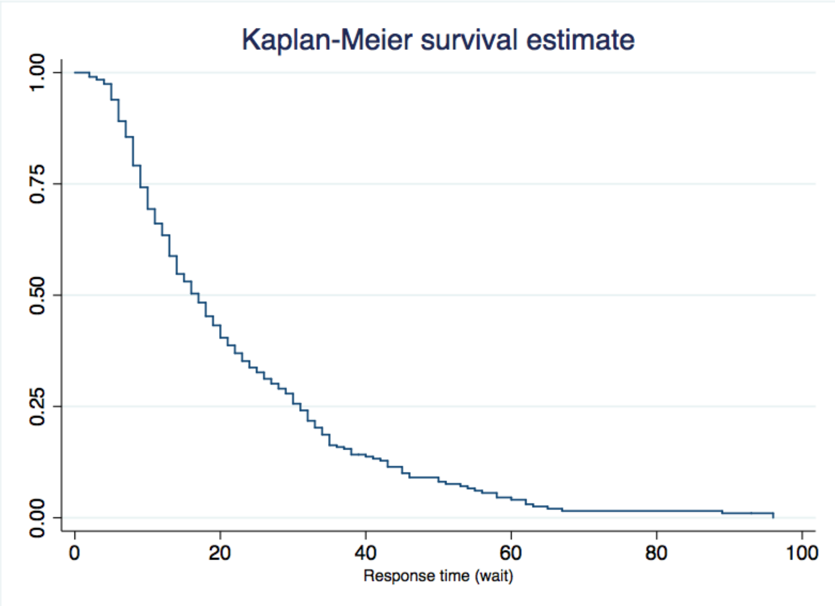
[8] Further methods can be used (e.g. parametric survival function estimation, but they are out of the scope of this paper.

Figure 3: The survival function, withdraw



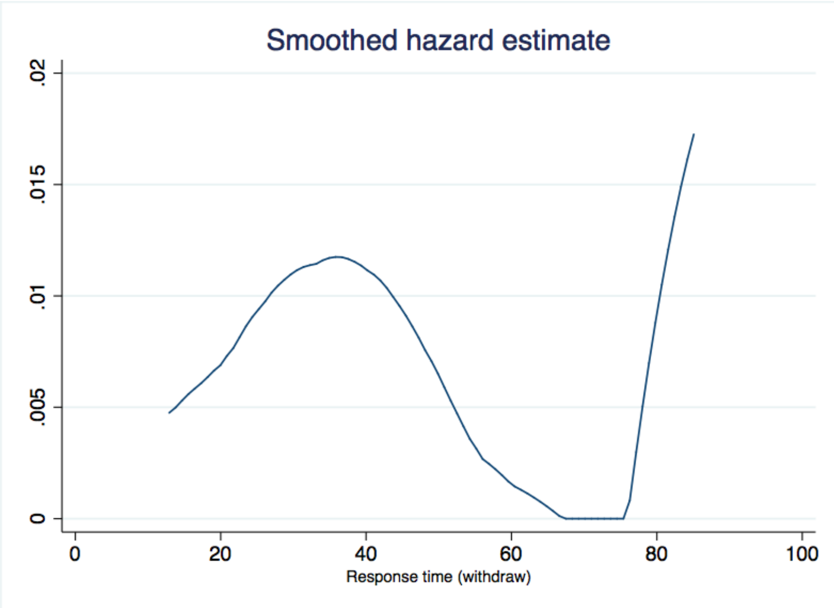
However participants with the right choice (Figure 4) tend to wait more. They are significantly making more decisions after the 25s benchmark.

Figure 4: The survival function, wait



Looking at the hazard functions strengthen this intuition. For withdrawing (Figure 5) participants the hazard rate peaks just before 40s, after it declines. However there are only two respondents above 45s response time [9].

Figure 5: The hazard function, withdraw



As far as the waiting participants are concerned their hazard[10] rate is also growing, but it peaks just before 60s. Intuitively this 20s lag means that the response time is much longer among people with the right decision (no surprise here). Moreover due to the (monotonic) increasing hazard function on the relevant interval, one can conclude that with the increase of thinking time the "hazard" of making the right decision grows.

In order to study what are the driving forces behind hazard functions, one can use Cox regression models. The main variable is the response time on the third position the explanatory ones are – as latter mentioned – the cognitive abilities, gender, risk aversion, uncertainty.

[9] Latter explains the significant jump in the end, caused by an outlier
[10] Hazard terminology might be misleading here, because the occurrence of the event here is beneficial

Figure 6: The hazard function, wait

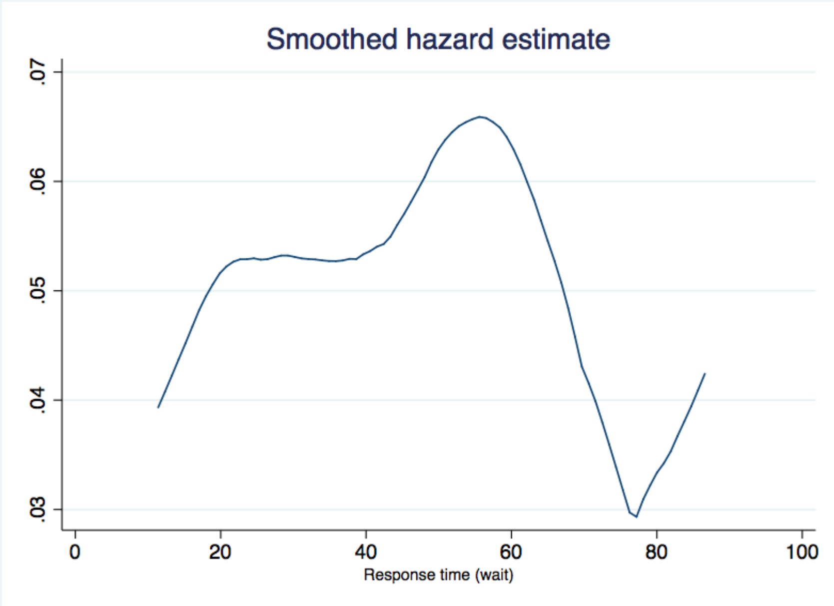


Table 6 shows the two regressions' output. Uncertainty (struncert2) is significant in both models. In the first case (withdrawing) it has a positive effect on the hazard function. Its magnitude is exp(1.114) = 3.046, which means that in case of uncertainty and holding all other explanatory variables fixed, the hazard of withdrawing increases by 204 percent. In case of waiting the direction of uncertainty is the opposite. Intuitively it is clear: with uncertainty and holding all other explanatory variables fixed, the "hazard" of making the right decision (waiting) is decreasing by 30.5 percent (since exp(-0.365) = 0.695). Moreover, risk aversion has a negative effect on making the right decision in the second model and the repetition of games (period) has a significant, positive effect on waiting but not withdrawing.

Table 6: The estimated Cox-models

VARIABLES	(1) withdraw	(2) waits
gender	-0.226	-0.205
	(0.455)	(0.153)
1.crt_sum	0.366	0.315
	(0.635)	(0.226)
2.crt_sum	-0.181	0.210
	(0.714)	(0.213)
3.crt_sum	-45.08	0.114
	(0)	(0.239)
riskav	-0.0824	-0.161**
	(0.195)	(0.0681)
struncert2	1.114**	-0.365***
	(0.494)	(0.124)
period	0.00115	0.0755***
	(0.0433)	(0.0144)
Observations	312	312

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Since uncertainty plays huge and significant role in hazard and survival[11] functions, their separated estimations are illustrated (Figure 7, 8, 9 and 10).

As far as the survival functions are concerned the figures are intuitively correct. In case of withdraw the more the uncertainty is, the steeper the survival function (Figure 7). The wait dimension is similar. In case of uncertainty at a given time point, the chance of not chosen the wait option is grater for respondents with uncertainty. This means that, for example at t = 20s around 30 percent of the respondents facing no uncertainty (blue line) has not chosen wait, on the contrary this value is around 45 percent for ones facing with uncertainty (red line).

[11] Survival function can be derived from hazard function and vica-versa.

Figure 7: The separated survival function, withdraw

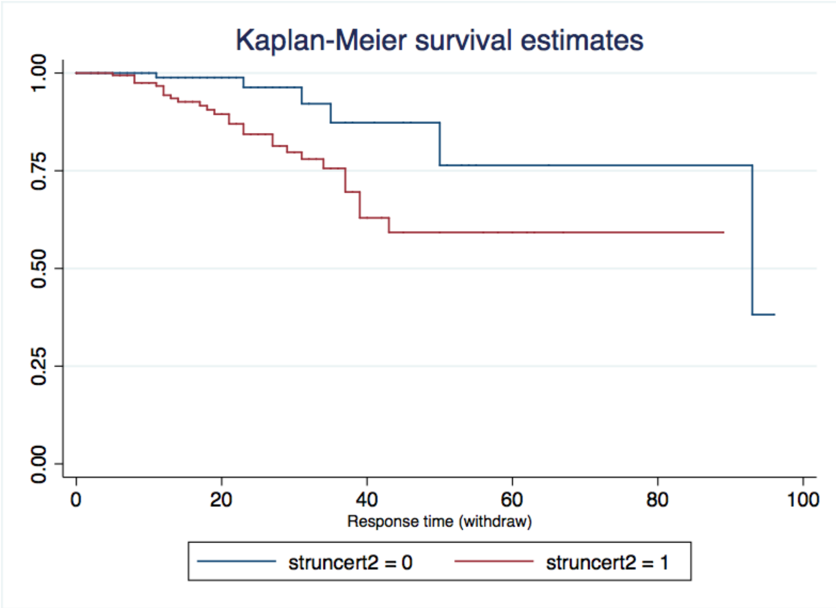
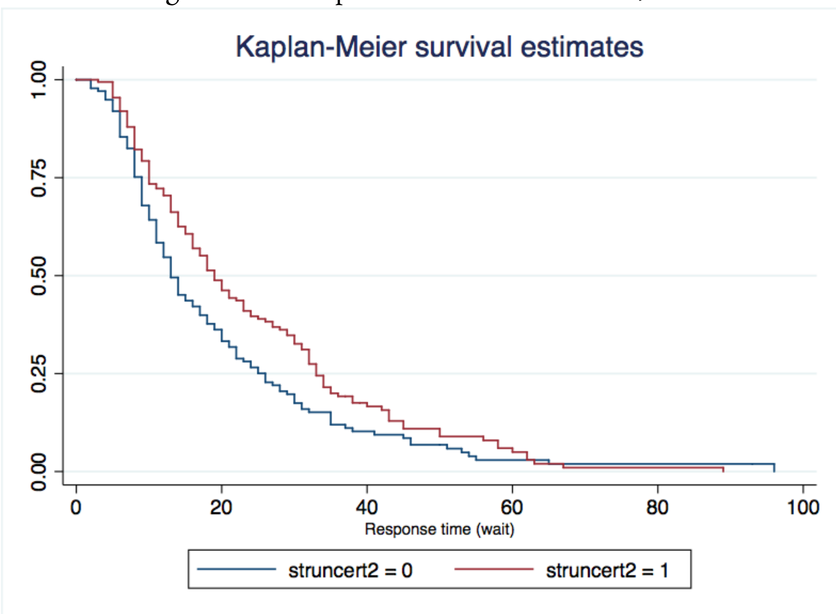


Figure 8: The separated survival function, wait



The different process can be also seen on the hazard functions. Withdrawing respondents are having significantly higher hazard rate, moreover their hazard rate stops just before 40s, which means that with uncertainty they made their wrong decision fast. The waiting segment decision making was almost balanced without uncertainty, however facing with risks respondents tend to make their decision in the final third of their time (peaked at 60s).

Figure 9: The separated hazard function, withdraw

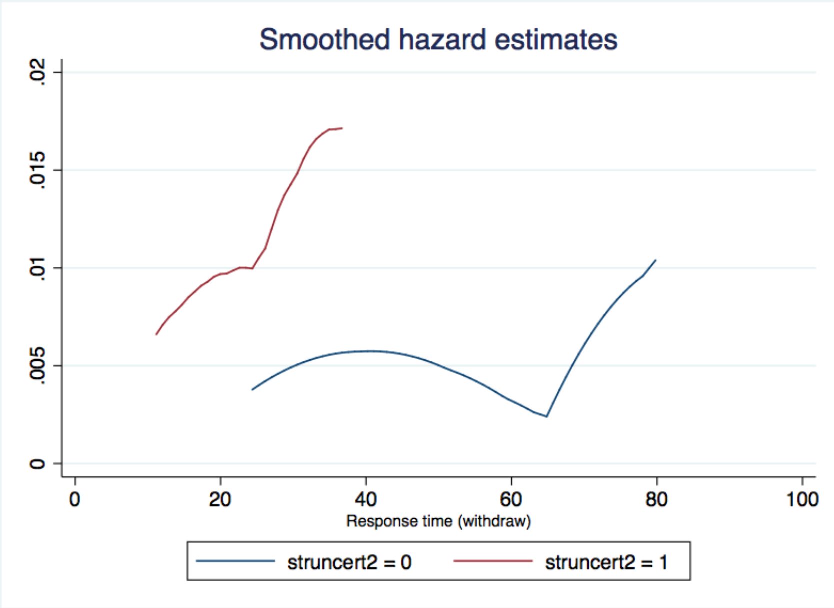
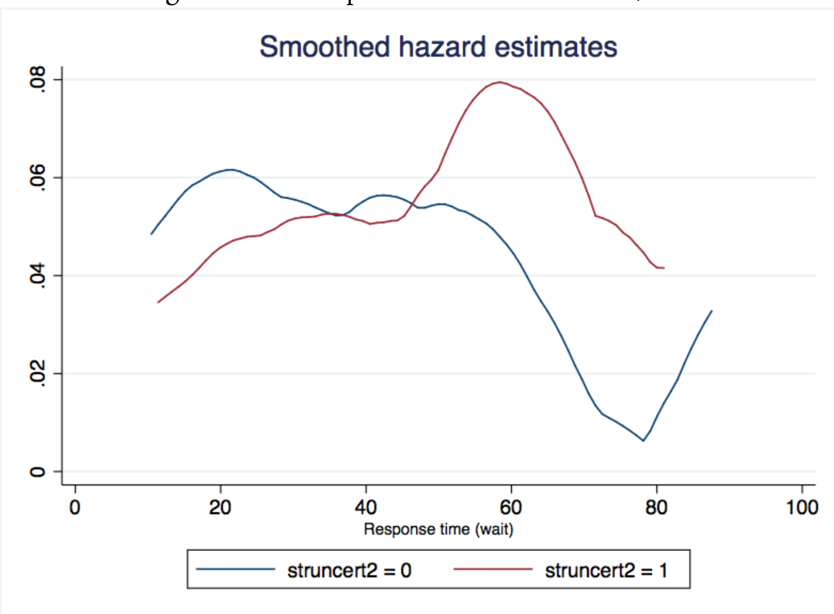


Figure 10: The separated hazard function, wait



6 CONCLUDING REMARKS

According to the estimations of this paper one can conclude, if the agent has a dominant strategy, ”thinking twice” – in the sense that thinking drives her to the right choice – is a valid recommendation. Moreover, looking at the survival analysis the dominant role of uncertainty is confirmed: even in the correct cases it has delayed the decision.

Nevertheless one should be concerned with this analysis’ limitations. Most notably, in this setting response time was not determined totally exogenously by the experimenter. Further research should focus on this exogeneity, in order to loosen the ex ante assumptions (more precisely, Assumption 2) [12]. Furthermore in this context response time was equivalent to thinking time, however one should not be fully concerned that the participants spent their time only with thinking.

[12] However latter assumption might be too strong, the negative effect is robust.

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