3. The process of choice in games*

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RESPONSE TIME AND STRATEGIC CHOICE

The study of response times (RTs) has a long history in experimental psychology going back to Donders (1868) who was interested in measuring the time that a particular hypothetical mental stage involved in a task can take. This was when the idea that response times can help to infer the mental processes behind psychological phenomena took root (Luce 1991). Since then 'mental chronometry' (Jensen 2006) was used by psychologists together with the choice or survey data to make inferences about the processes underlying choices or to analyze behavior under time pressure. As it was recently stated by Ariel Rubinstein (2007, 2016), measuring response time allows us to 'open the black box of decision making' (Rubinstein 2007, p. 1243). The same sentiment is shared in a thorough review of recent experimental economics studies that use RTs (Spiliopoulos and Ortmann 2018).

In spite of the view that RT can be utilized not only in testing hypotheses related to the process of choice but also in order to better understand preferences (Konovalov and Krajbich 2019a), its usage in experimental and behavioral economics was limited, if existent, until very recently (a known exception is Wilcox 1993). The tide started to change with the advances in models of procedural rationality and studies of strategic sophistication and deliberation costs (starting with Stahl and Wilson 1994, 1995 and Nagel 1995), which made RT a natural candidate for a choice characteristic that allows uncovering of the details of the decision process under the assumptions of bounded rationality. Another reason for the introduction of RT to experimental economics is the emergence of neuroeconomics, which has brought many psychological and neuroscientific research tools to light, including mental chronometry.

Response Time in the Models of Decision Process in Games

There are two broad classes of models which make explicit predictions about the RT of choice. The first is dual-process theories (DPTs) (Kahneman 2003), which assume the presence of two decision systems: fast intuitive system and slow deliberative system. The former system (type 1) is useful in situations when decisions should be made instantaneously. It involves 'hot', emotional responses and has most likely evolved to make choices in rapidly changing situations. The latter system (type 2) is slower and 'cold; and is helpful in situations when there is no time pressure and complex reasoning can help to make the choice.

The second class of theories comes under the titles of sequential sampling, information accumulation or drift-diffusion models (DDMs) (Ratcliff 1978; Smith and Ratcliff 2004; Krajbich et al. 2015a). Here the process of choice among several options is explicitly modeled as a random process. The idea comes from the neurophysiological observation that neurons in the brain are noisy and, thus, as information about the available options is accumulated, the more desirable option is chosen with higher probability. Mathematically this is represented by a random walk with drift and two barriers, A and B (in the event of two options). The crossing of one of the barriers by the random walk represents the time point of making the choice (A or B). Here the steeper the drift, the higher the difference in utilities of the two options; the greater the difference in utilities, the faster the choice will be made. In models of this type it is possible to make explicit predictions about the speed–accuracy trade-off involved in a decision. If the time available for choice is limited (exogenously or endogenously), then the resulting choice will be fast but not very accurate. However, if the time is not constrained, the decision will be slow and the probability of choosing the best option will be high.

The two classes of models raise different questions and utilize different types of data. Both are also subject to criticism. According to Keren and Schul (2009), dual-process theories are never precisely formulated: what type 1 and type 2 systems are supposed to represent in any given task is usually decided by the researcher, who uses his or her own intuition without resorting to any objective procedure. This can lead to far-fetched conclusions which ignore other possible explanations. Rustichini (2008) provides an overview of pros and cons of dual-process theories and unitary theories, where the latter assume that there is only one system that makes decisions by aggregating information available from different sources. He comes to a conclusion, similar to that of Keren and Schul (2009), that one caveat of the dual-process theories is that the characteristics of the type 1 and 2 systems change depending on the experiment (for example, in some instances the type 1 system is impulsive and in others reactive to fear).

Drift-diffusion models are criticized for putting too much emphasis on speed–accuracy trade-off. For example, Pennycook et al. (2016) notes that in choice situations where there is conflict (for example, when the stereotype is not in line with base-rate information; De Neys and Glumicic 2008), the RT, if seen in the light of DDMs, might be misinterpreted since RT increases when conflict is introduced even if discriminability of the options stays the same. Thus, RT might be modulated not only by the discriminability of the options but also by other factors.

Studies Based on Dual-Process Theories

One of the most cited but, at the same time, controversial studies of strategic choice that tests hypotheses based on dual-process theory is Rand et al. (2012). Their study uses a series of standard one-shot public goods (PG) games with four players in order to establish a connection between RT and the contributions to the public good (data were collected on Amazon Mechanical Turk). With the sample of 212 subjects, Rand et al. (2012) find that high contributions are associated with low RT and low contributions with high RT (RT is measured as the time between the appearance of the decision task on the screen and the submitted answer). In addition, if RT is forced to be low (time pressure) then contributions tend to be high. Conversely, if RT is forced to be high (time delay), the contributions are low. Rand et al. (2012) conclude that cooperative behavior is intuitive and that the choice to free ride takes mental effort and time.

The results of this study came under close scrutiny after its publication. Tinghög et al. (2013) and Verkoeijen and Bouwmeester (2014) both failed to replicate the results from Rand et al. (2012). These authors noted aberrations with data analysis (the exclusion of 50 percent of subjects from analysis based on their inability to respond on time) and the presence of many uncontrolled factors that can influence RT (for example, subjects could forget the rules of the game between repetitions).

Another line of critique comes from experimental economics studies. Recalde et al. (2018) tested the main conclusion of Rand et al. (2012), that generosity in PG games is intuitive. Recalde et al. (2018) used modified PG games in which unique dominant strategy equilibrium is in the interior of the action space for each player.[1] They showed that in this case fast decision makers' choices are not influenced by the position of the equilibrium. This implies that for the PG games with equilibria in the lower half of the action space fast decision makers tend to be more generous than slow decision makers. However, if equilibrium is in the upper half of the action space, fast decision makers become less generous than the slow decision makers. This and additional tests make Recalde et al. conclude that the choices of fast decision makers are best explained by mistakes (including the prevalence of choices of the actions which are dominated from both individual and group perspectives) and are not driven by intuitive generosity. Similar conclusions about mistakes are reached in an experimental study that considers beauty contests (Kocher and Sutter 2006). Here, fast decision makers are less efficient and are slower to reach equilibrium in the repeated setting which is also attributed to higher mistake rates.[2]

In spite of this criticism, other studies support the intuitive cooperation hypothesis. Cappelen et al. (2016) examine response times in the dictator game (DG) with careful control over the factors that might influence RT. In particular, Cappelen et al. (2016) conduct additional tests on swiftness of choice and cognitive ability. Swiftness is measured by the time it takes subjects to answer three standard demographic questions. Cognitive ability is measured by a 20-item progressive Raven test. Cappelen et al. (2016) come to the conclusion that, after controlling for swiftness and cognitive ability, the cooperators are still faster than free riders. Nielsen et al. (2014) obtain the same result with a large-scale PG game and conclude that free riders act slower than cooperators. It should be mentioned that these two studies are not immune to the 'fast decision makers make more mistakes' critique discussed above. Moreover, the results for the DG should be considered with caution: Tinghög et al. (2016) conducted large-scale experiments with around 1400 subjects from three countries and did not find any differences in giving choices in DGs under time pressure or cognitive load, which casts doubts on the findings of Cappelen et al. (2016).

Grimm and Mengel (2011) look at ultimatum game (UG), where they deliberately delay the response of the second movers by around 10 minutes (the subjects answer a questionnaire before their response decisions). They find that after the delay there are many more accepting choices than in standard setting. This does not per se support the intuitive cooperation hypothesis, but does demonstrate that rejections in UG do result from fast emotional reaction that has to be expressed immediately after observing the choice of the proposer. In this setting, where only two actions are available, the change in behavior can hardly be attributed to the mistakes made by fast decision makers. These findings, thus, support the dual-process theory.

Nishi et al. (2017) extend the intuitive cooperation hypothesis in a follow-up experiment to Rand et al. (2012) in part as a response to the criticism just mentioned. Nishi et al. (2017) put forward the social heuristics hypothesis (SHH) which postulates that people are fast at choosing options that they use in everyday life, be they cooperative or not. In the environments where reputation plays a role, cooperative behavior might be ubiquitous (or constitute a social norm), while selfish choices are uncommon. On the contrary, in environments where selfishness is a norm, cooperative choices will be considered unusual.[3] Thus, from the perspective of dual-process theory, we should expect fast intuitive reaction when an action representing a norm is chosen and slow deliberative reaction when an action which violates a norm is preferred.

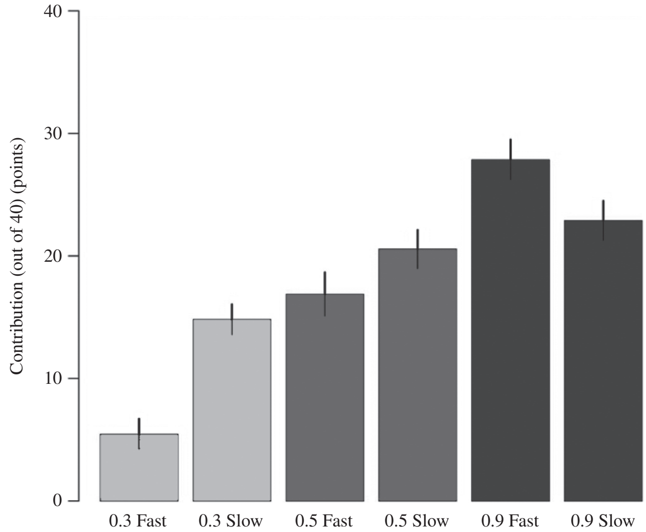
Nishi et al. (2017) conduct repeated social network PG games experiments in the US and India (using Amazon Mechanical Turk). First, they find that overall cooperation rate in the US is significantly higher than in India (75 percent versus 44 percent in the neutral environment, and 88 percent versus 37 percent in the cooperative environment), which suggests that the common behavior is different in the two countries (cooperation in the US and defection in India). Second, Nishi et al. (2017) show that the negative correlation between cooperative choices and response times in the US is reversed in India: selfish choices are made faster there. These findings directly support the SHH and provide evidence of the primary role of social norms in decision making. However, completely different interpretation of the differences between the American and Indian data is possible if RT is considered in the light of DDMs, which we turn to in the following section.

Studies Based on Drift-Diffusion Models

Not many studies of strategic choice utilize DDM as the hypothesis-generating theory. Drift-diffusion models were originally used in perception studies in order to predict how the perceptual systems in the brain discriminate between two visual stimuli. Later, these models were adapted to studying individual choice. Many studies have demonstrated a remarkably good fit of DDM to the binary value-based choices, in particular, the resolution of speed–accuracy trade-off was shown to be matched very well (for example, Milosavljevic et al. 2010 fit DDM to the value-based decision-making data under time pressure). This literature is still in its infancy and not many attempts have been made to apply DDM to strategic situations.

Nevertheless, Krajbich et al. (2015b) used DDM to clarify the connection between RT and choices in DGs and PG games. In part, their goal was to show that the conclusions about RT in strategic environments made under the assumptions of dual-process theories should be taken with caution. They conducted several experiments to show that reverse inference results, which label, say, cooperative behavior as intuitive based on short RT, might be an artifact of the experimental design. Their argument, derived from DDM, involves the notion of discriminability: the less is the difference in utilities from the available options, the longer the choice process will take. Krajbich et al. (2015b) conducted an experiment where subjects were presented with a series of mini DGs that varied in the amount of money a subject should have sacrificed in order to increase the payoff of the receiver. To estimate the difference of the values derived from the choices, Krajbich et al. (2015b) fitted inequality-averse utility function to the choices of each subject. It follows directly from DDM that pro-social subjects should make their preferred choice (more money to the receiver) quicker than the selfish choice. The opposite holds for selfish subjects: they should make their preferred selfish choice quicker. The data of Krajbich et al. (2015b) support DDM predictions: the correlation of the RT with the pro-social choice has opposite signs for pro-social and selfish subjects. Thus, in an experiment, where RT for choosing selfish or pro-social actions are compared, the faster RT will be found for the action which is chosen more often. For example, if there are more selfish than pro-social subjects in the experiment, the selfish choice will have a shorter RT and vice versa.

Krajbich et al. (2015b) use this intuition to revisit the results of Rand et al. (2012). They run the same public goods experiment, but consider three levels of the marginal per capita return from the public good. Figure 3.1 presents the results. Krajbich et al. (2015b) demonstrate that



Note: Consistent with DDM, in low return condition fast contributions are lower than slow ones (two-sided t-test, $p = 0.00001$), while in the high return condition fast contributions are higher than slow ones (two-sided t-test, $p = 0.03$).

Source: Krajbich et al. (Krajbich et al. 2015b, fig. 3.4).

Figure 3.1 Average contributions to public good in three experiments with different marginal per capita returns (MPCR = 0.3, 0.5 and 0.9)

with the low return the selfish option is faster than the cooperative option, whereas with the high return the cooperative option is faster (as in Rand et al. 2012).

Thus, Krajbich et al. (2015b) conclude that, in line with DDM, the distance in utilities of the two options and the composition of the subject pool determine which type of action is faster: if a great deal of monetary units have to be forgone in order to increase group payoff, selfish choices will be faster as selfish subjects will find it easier to make this choice. On the contrary, if few monetary units should be forgone to increase group welfare, pro-social action will be faster since it will be simpler for pro-social subjects to choose.

Finally, DDM interpretation of the data might also explain the difference in RT observed in Nishi et al. (2017), discussed previously. The Indian population seems to have more selfish types than the American population, thus, according to the argument above, we should expect faster RT for selfish action in India and faster RT for pro-social action in the US, exactly what was found in Nishi et al. (2017).

Studies Based on Response Competition Dual-Process Theories

Some researchers note that although the DPT critique of Krajbich et al. (2015b) is on target, it completely ignores the diversity of models and approaches in DPT literature and, thus, the results of Krajbich et al. (2015b) should not be taken as an ultimate falsification of DPT. In particular, the arguments of Krajbich et al. (2015b) go against the (inverse inference) practice of labeling fast RT choices as intuitive and slow RT choices as deliberative. However, as

Pennycook et al. (2016) observe, there exist other types of DPT which are not at all concerned with the intuition–deliberation dichotomy. A great deal of attention has been paid to the idea of the competition or conflict between two systems for the right to make a choice.[4] For example, in base-rate problems a conflict is artificially created between the overwhelming information that someone, say Paul, is a nurse and his stereotypical look of a doctor. In these studies (for example, De Neys and Glumicic 2008) it is shown that, in guessing who Paul actually is, the majority of subjects go with the stereotype and that the RT in the problems with conflict is longer than in the problems without it no matter what action is eventually chosen. Response competition DPT gives an answer to the question of why RTs are longer: the conflict between two systems causes the type 2 deliberative processing.

This type of effects on RT is not necessarily inconsistent with DDM. The idea of a conflict between options is investigated in at least two studies which involve strategic interactions. Evans et al. (2015) conducted several experiments with one-shot prisoner's dilemma (PD) and one-shot and repeated PG games. They found that RTs follow the inverted-U pattern, namely, extremely selfish and extremely cooperative choices were fast, whereas choices in between the two extremes were slow. In addition, unlike in Rand et al. (2012), this effect did not disappear with repetition. Response competition DPT explains these results as a consequence of a conflict between a system that advocates selfish choice and a system that prescribes cooperation. When one of the two systems is dominating, the conflict is quickly resolved, while it takes longer for the resolution when the two systems are of comparable strength. Furthermore, these findings are exactly in line with the argument of Krajbich et al. (2015b), which stipulates that subjects with extreme preferences for either selfishness or pro-sociality should make decisions faster than those with mixed preferences.

Similar results are reported by Piovesan and Wengström (2009), who measure RTs in a sequence of mini DGs played by each subject. The DGs varied in the degree of inequality of the allocations and whether a dictator was rich or poor (dictators were getting more or less money than receivers). Piovesan and Wengström (2009) found that RT was correlated with the social complexity of the choice: selfish choices were reached faster than choices that necessitated social considerations.[5] In addition, it took poor subjects longer to reach the decision than rich subjects, which suggests the involvement of envy in the decisions. All this taken together supports the conflict resolution hypothesis of longer RTs.

Inferences Using Reaction Time

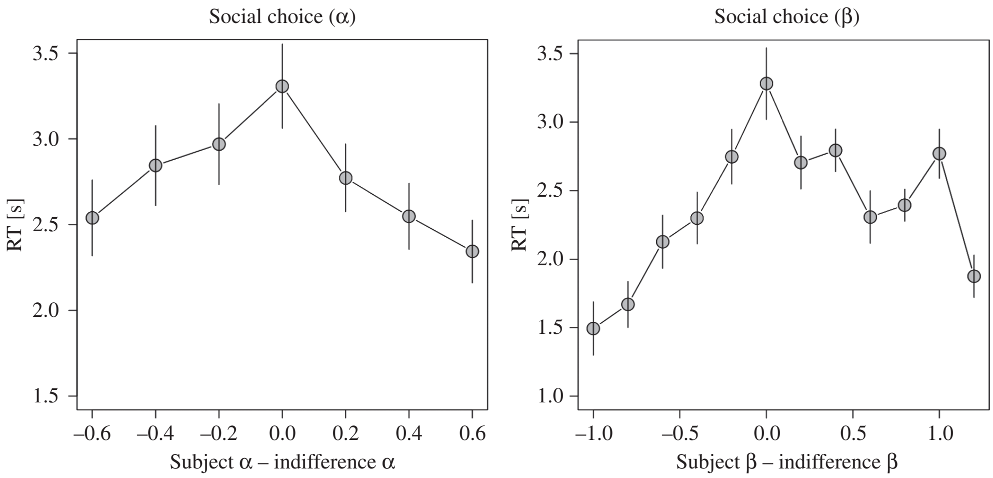
The studies mentioned up to this point were mostly concerned with the consistency of theoretical accounts with observed data. There is, however, a growing literature where an attempt is made to use RTs as signals of decision makers' characteristics. These studies can be divided into two categories: (1) RTs are used by experimenters to infer subjects' preferences; and (2) RTs are used by subjects to infer others' motives or as signals revealing private information.

In the first category are the studies by Rubinstein (2007, 2013, 2016), who used the unique dataset with tens of thousands of observations obtained from http://gametheory.tau.ac.il (accessed 9 July 2020). It was used to create a typology of subjects using their RTs in 10 games. Later, the predictive power of this typology was investigated on a set of unrelated games. First, a very large number of anonymous observations (2000 to 13 000 subjects in each game) from http://gametheory.tau.ac.il (accessed 9 July 2020) were used to measure the mean RTs of the actions taken in the 10 games (eight normal form games and two extensive form: ultimatum and centipede). The RTs then were divided into two categories: below median and above median. The actions with below-median mean RTs were labeled instinctive and those with above-median mean RTs contemplative (notice that the procedure is completely objective and does not involve any ad hoc assumptions). Next, a series of experiments was conducted where subjects played the same 10 games. The contemplation index (CI) for each subject was calculated as a proportion of games in which a subject took a contemplative action. It was then demonstrated that, in a set of unrelated games, there was a correlation between action choices and CI of the subjects even when the mean RTs of the choices where not significantly different. This shows that the division of the subjects in accordance with their choosing instinctive or contemplative actions can predict their choices in unrelated games.

In another study Konovalov and Krajbich (2019b) use RT information to infer subjects' individual preferences. They use the insight from DDM that difficult choices (low discriminability) should be slower than easy choices (high discriminability). To validate this premise, Konovalov and Krajbich (2019b) collected data in three choice experiments including one with a sequence of mini DGs with varying payoff allocations (akin to Piovesan and Wengström 2009). From the data, the utility function parameters were first estimated for each subject (for DG, the parameters of the utility function with inequality aversion). Then, for each choice task of each subject, the difference between the utility parameter of the subject and the parameter which would make the utilities of the options the same was calculated and treated as a measure of task complexity for that subject: if the absolute difference was small the task was deemed complicated; if the absolute difference was large, the task was considered easy. Konovalov and Krajbich showed that the difficulty of the tasks measured in this way was strongly correlated with the RT: difficult tasks took longer (Figure 3.2 illustrates this).

In the next step, Konovalov and Krajbich (2019b) demonstrated that information about RT can be successfully used to deduce preferences even with very little data. They showed that the utility parameter inferred from a single choice and RT was a good predictor of the subsequent choices. In addition, RTs allowed for the identification of preferences from choice tasks where the majority or all subjects chose the same option. Overall, this study demonstrates the great potential of using RTs in decision making experiments.

Two studies utilize RTs in order to test the hypothesis that subjects are able to use information that RTs convey about other players' unobserved preferences or private information. Frydman and Krajbich (2019) investigate choices in a classical information cascade task in two conditions, with and without subjects' observing RT of the previous player. They make two important observations: (1) from the perspective of DDM, RTs in information cascade do deliver additional information about the private signal of a player when her choice is in line with the cascade's history of choices; (2) subjects in the experiment are able to use this information contained in RT to correctly infer the private signal. The first observation builds upon the following argument. Conditional on player's choice to be in line with the majority, when his or her private signal is congruent with the previous choices, the decision is easy and should be made quickly. When, however, the private signal is incongruent, the choice is hard and should take longer. Therefore, RT reveals information about the private signal. Frydman and Krajbich (2019) showed that the subjects could extract this information from the RT and change their own choices accordingly.



Note: The inequality-averse social preferences parameters α and β were estimated for each subject (Fehr and Schmidt 1999), where α parametrizes the disutility from disadvantageous inequality and β the disutility from advantageous inequality. After that, indifference α and β were calculated for each game, that is, α and β made the utility from both options the same. For each game and a particular choice, the absolute difference between subject's parameters and the indifference parameters was taken as a measure of the choice complexity. The graphs demonstrate that RT increases as the subjects' preferences get closer to indifference.

Source: Konovalov and Krajbich (2019b, fig. 10.2).

Figure 3.2 Subjects made 120 choices in a series of mini DGs with two options

Evans and van de Calseyde (2017) follow one of the studies discussed above (Evans et al. 2015) and investigate what type of information about others subjects are able to infer from observing RTs. They use the data previously collected in a PG game experiment to tell subjects the RTs of choices and then ask them to evaluate the motives of the players on several Likert scales. Evans and van de Calseyde (2017) find that short RTs are associated in subjects' minds with the extreme choices, either full or zero contribution, and long RTs with intermediate contributions. This is in line with the actual behavior reported in Evans et al. (2015). More interestingly, when the subjects were told that the players in the actual PG game were exogenously time constrained, the responses became mixed without any clear pattern. These findings indicate that RTs, when unconstrained, can be informative about the incentives and the choice process of others in social dilemmas.

EYE AND MOUSE MOVEMENTS DATA IN STRATEGIC INTERACTION

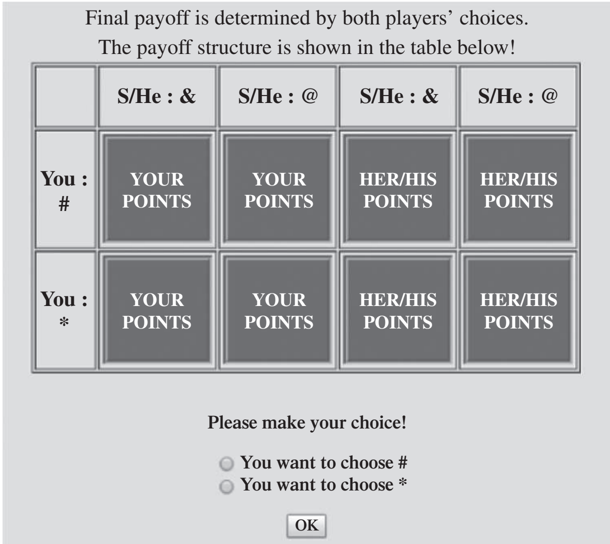
Visual Attention in Eye-Tracking and Mouse-Lab Paradigms

The primary purpose of the visual process is to derive meaning from the world in order to direct our actions. This is a dynamic process that is conducted by the brain through the visual system and in which attention plays a crucial role. According to Duchowski (2007), attention involves a cyclical procedure composed of different stages. In a situation in which a stimulus such as an image is observed by a person for the first time, attention is usually driven by the characteristics of the visual scene. This is termed bottom-up attention, in which an individual starts observing the entire scene through a low-resolution peripheral vision while the important elements of the scene are captured in the field of view. In the first stage, the features that are considered interesting are selected for a subsequent, deeper analysis. The second stage includes disengagement of the attention from the less attractive elements and the repositioning of the eyes to capture the stimuli that most attracted the attention (selective attention). Finally, when the fovea is repositioned to the area that attracted the most attention, all the features of these regions of interest can be inspected at high resolution. This is a bottom-up model of visual attention that does not take into account the situations where the eye movements are guided by the voluntary intention to capture or attend to a specific part of the scene. In this regard, Yarbus (1967) highlighted the role of top-down factors in modulating the eye movement patterns used by the observer to acquire information from a scene. When a stimulus, such as an image, is observed by a person for the first time, the eye movements should be driven by bottom-up processes. Conversely, top-down factors should have a prominent role in modulating the patterns of eye-movement as soon as the individual becomes more familiar with the stimulus.

That attention can be mediated by bottom-up or top-down mechanisms has important implications for the interpretation of the process data because an observed information search pattern may be the result of a predetermined information search strategy (top-down analysis) or mainly determined by some features of the visual scene (bottom-up analysis). In eye-tracking experiments, the characteristics of the task and of the decision maker may significantly affect how attention is allocated in a visual scene. For example, a bottom-up analysis may be promoted by the presence of attractors or focal points (Devetag et al. 2016). Conversely, the adoption of routines may promote a more stable and systematic visual analysis.

In classical mouse-laboratory experiments, features of the scene, such as focal points and attractors, cannot drive attention because the information (presented on a computer screen) is hidden in opaque boxes and can be revealed only using the mouse pointer (Figure 3.3). The way in which information is revealed in a typical mouse-laboratory study can be set by the experimenter and varies depending on the type of task and the object of study. For example, information can be revealed (1) when the pointer is moved into the box, (2) when the pointer is moved into the box and the left button of the mouse is pressed, or (3) when the pointer is moved into the box and the left button is held down. Mouse-laboratory techniques can provide high-resolution temporal data about the location of the pointer (in terms of pixels) and many other analysis metrics such as the number of times a certain box is opened and for how long. In addition, more advanced mouse-tracking techniques can retrace the mouse's trajectories, and examine velocity and acceleration.[6] In general, using a mouse-laboratory paradigm a researcher can understand how, when and what information is processed by the participant, and how the decision processes evolve over time.

Some studies have noted that the mouse-laboratory paradigm may itself have an effect on the information search process (Billings and Marcus 1983; Maule, 1994; Lohse and Johnson 1996; Glöckner and Betsch 2008; Franco-Watkins and Johnson 2011). For example, attention cannot be affected by peripheral information, and the way it is allocated in a given visual scene is largely based on top-down processes. Glöckner and Betsch (2008) argue that this research method, in some instances, promotes deliberation and prevents the activation of automatic decision-making processes. Moreover, the mouse-laboratory method significantly



Note: In this example, participants (the row players, You) can see the payoffs by moving the cursor over the boxes. The payoffs of the participants (Your points) are located in the two left-most columns. The payoffs of the counterpart (Her/his points) in the two right-most columns. It is possible for the participant to have only one box open at a time. When the participant move the cursor outside the opaque area, the box closes automatically.

Source: Adapted from Spiliopoulos and Ortmann (2018).

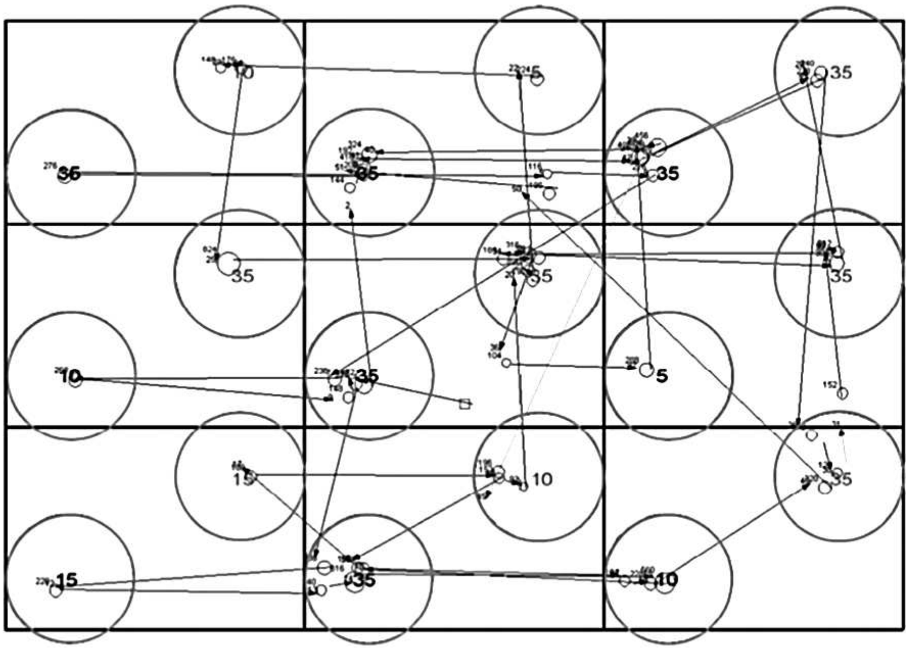
Figure 3.3 Mouse-laboratory screenshot of a two by two one-shot game

increases the amount of time needed to acquire information compared with the eye-tracking method. In eye-tracking paradigms a participant can acquire information in a more natural way, whereas in mouse-laboratory paradigms the participant is induced to be engaged in a serial consideration of information. Unfortunately, the use of eye-tracking apparatus is usually costly and the data collection is limited to one participant at a time, which makes mouse laboratory a viable alternative despite its drawbacks.

Eye-Tracking System

The eye-tracking system measures the point of gaze (where a subject is looking) and the motion of one or both eyes relative to the head position. The standard sampling rate of an eye-tracker varies from a minimum of 60 Hz, to a maximum of 2000 Hz. Modern eye-trackers identify eye movements and gaze locations by using the contrast between the center of the pupil and the iris. Moreover, they can create a corneal reflection using an infrared non-collimated light. The system creates a vector using these two features and, after a calibration procedure, computes gaze intersection with a surface.

Common analysis metrics include fixations location and their duration, saccades directions, velocities and amplitudes, smooth pursuit and transitions-based parameters between fixations and/or region of interest. Eye-tracking systems also allow to measure how much pupils dilate (expand in width and area). Fixations and saccades are excellent measures of visual attention

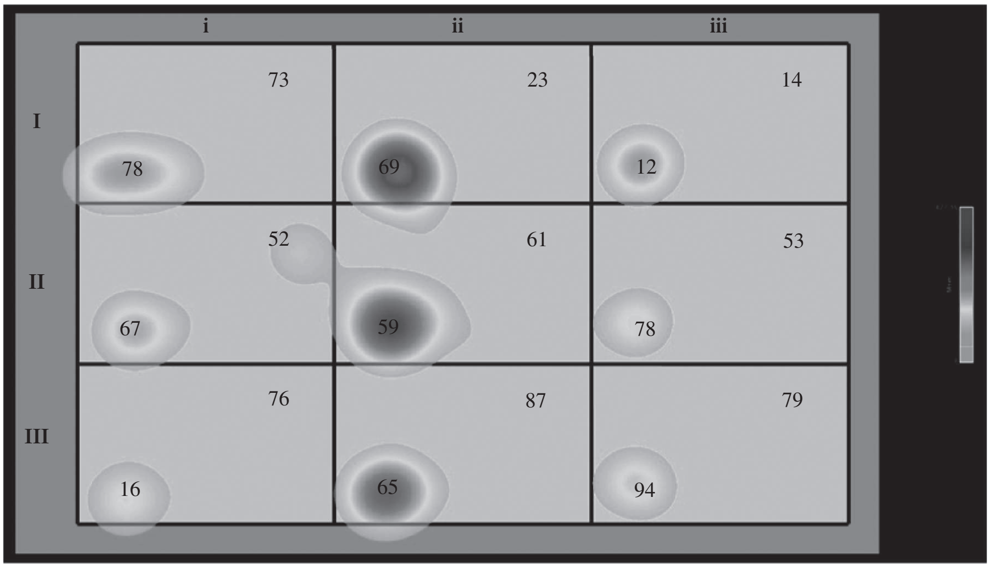


Note: The background image is the game shown to the participant. The circles indicate the areas of interest defined by the experimenter for the analysis of the eye-tracking data. The small circles indicate the fixation locations (the size of the circle is proportional to the fixation duration), whereas a number next to a circle indicates the fixation duration. Lines indicate the saccades, and the arrows indicate their directions.

Figure 3.4 This example shows the event data, such as fixations and saccades of a row player, recorded during a trial of a two-player, three-by-three, normal form game

and expressed interest. During fixations, the eyes extract information from the visual scene for further processing. During saccades, visual perception is suppressed (Matin 1974); however, differences in speed and accuracy of the eye saccades can affect the amount and the quality of information processed. Smooth pursuit eye movements allow the eyes to keep the visual projection of a moving object continuously on the center of the fovea.

In general, eye-tracking data provide information about which elements of the visual scene participants take into account, how long they look at a certain areas of interest (AOI), and in what order they look at the available information. Figure 3.4 describes the main parameters that can be acquired by using an eye-tracking device. The circles represent the AOIs, defined by the experimenter to identify when the participant is looking at one particular visual element on the screen. The definition of the AOIs is important to allow a detailed examination of events data such as fixations and saccades (represented by small circles and lines respectively). Areas of interest are sub-regions of the displayed stimuli that can be used to understand whether a respondent is acquiring certain information. They can also be used to measure how much time passed from stimulus onset until respondents looked into the region (time to first fixation), how much time the respondents spent in the region, how many fixations they had, and the number of times the respondents returned to look at that area (number of runs). It is also



Note: This example shows the data on fixation duration of a respondent playing a series of three-by-three matrix games. The example shows that the respondent (row player) focuses his or her attention on his or her own payoffs and does not take into account the payoffs of the counterpart (column player).

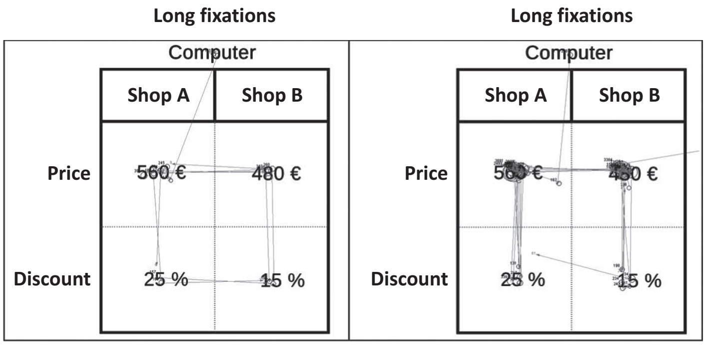
Figure 3.5 Data on fixation counts and fixation durations can be visualized using heat maps

possible to generate heat maps of fixation densities for single respondent as well as for a full study of several respondents (Figure 3.5). Eye-tracking heat maps are aggregations of fixations that reveal the distribution of visual attention. This is an excellent method to visualize which elements attract more attention than others.

The analysis of eye-tracking data can provide a lot of information about attentional and cognitive aspects of decision making and can help researchers in the evaluation of alternative theories. For example, a decision-making process that requires the acquisition of particular information, cannot be pursued when this information is not acquired (Johnson and Camerer 2004). At the same time, there is plenty of evidence showing that the order of information acquisition (the lookup pattern) is informative of the decision rule adopted and predictive of the decision (Johnson et al. 2002; Polonio et al. 2015).

Decision-making processes can be investigated also measuring the length of fixation and the pupil dilation. For example, longer fixations are associated with cognitive difficulty, such as deliberate consideration of information and planning (Velichkovsky 1999; Velichkovsky et al. 2002; Glöckner and Herbold 2011; Graffeo et al. 2015). Short fixations are typically related to simpler processes of visual perception, such as exploration of the environment (Figure 3.6).

Pupil dilation is an index of cognitive difficulty, stress, arousal and pain, which has been extensively used in the lie detection literature to infer deceptive behavior (Berrien and Huntington 1943; Janisse 1973; Heilveil 1976; Bradley and Janisse 1979, 1981; Janisse and Bradley 1980; Lubow and Fein 1996; Dionisio et al. 2001; Wang et al. 2010). Hess (1972) reported that pupil dilation occurs between 2 and 7 seconds after the presentation of emotional stimuli. In cognitively demanding tasks, pupil dilation reaches its peak 1–2 seconds after



Note: In this example, an identical product was on sale in two shops with different initial prices and discounts. The respondents were asked to choose the best option. The size of the circles indicates the length of fixations, the lines indicate the saccades. A correct procedure to compute the final prices requires the decision makers to compare, for each option, the initial price with the associated discount and engage in a mental calculation. The left-hand side of the figure shows eye movements of a respondent who used a simple comparison procedure to choose between the two shops. When one of the alternatives yielded a higher discount with a lower initial price, this decision maker chose that option. Alternatively, when one option yielded higher discount and another option lower initial price, the respondent selected the option with the higher discount. This simple decision strategy did not require long fixations. The right-hand side of the figure shows eye movements of a respondent who engaged in the calculation of the final prices. This complex cognitive operation required the respondent to keep the gaze on the most relevant information (the initial price) until the end of the mental calculation.

Source: Adapted from Graffeo et al. (2015).

Figure 3.6 Eye movements of two respondents while making a decision to purchase a product

trial onset (Beatty 1982) and contracts gradually (Kahneman and Beatty 1966) or instantly (Bernhardt et al. 1996) once the response is made.

In the following we take a more detailed look at how mouse laboratory and eye tracking can be used to inform economic theories. In particular, we focus on how process data can help to test different game-theoretic models.

The Relevance of Process Data for the Evaluation of Different Theories

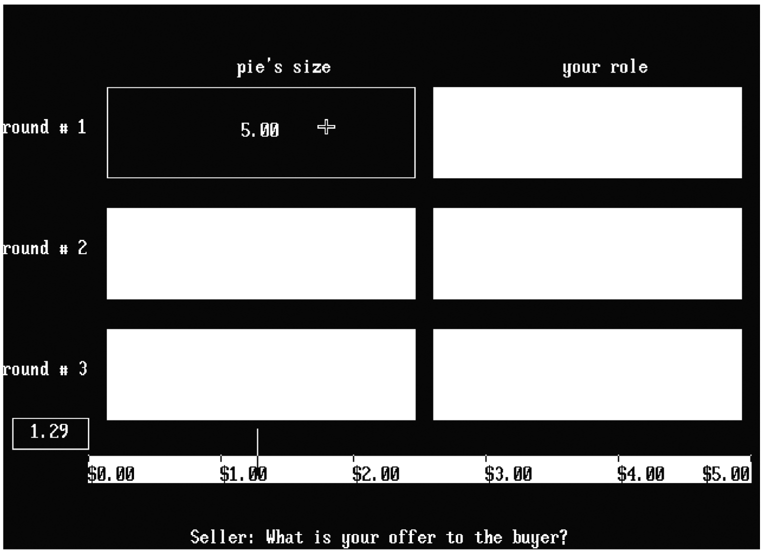
A fundamental question in game theory is why players sometimes deviate from equilibrium strategies, especially in situations where players do not have clear precedents (one-shot games). Many theories of bounded rationality were developed in an attempt to provide more accurate predictions of players' behavior than those provided by equilibrium analysis alone. Some studies have begun to evaluate these theories by combining information about process data with observed choices. The advantage of using process data is clear, since bounded rationality theories make precise assumptions about processes or factors that lead to out-of-equilibrium decisions. For example, McKelvey and Palfrey's (1995) quantal response equilibrium (QRE) relaxes optimization, but maintains the assumption of correct beliefs. The model assumes that players form accurate beliefs about the expected action of their opponent, but best responses are not played with certainty because players respond noisily to expected payoffs.[7] Similarly, in cursed equilibrium (CE), it is assumed that players are able to estimate the distribution of actions chosen by other players, but sometimes deviate from equilibrium because they do not fully take into account the correlation between others' decisions and private information (Eyster and Rabin 2005). The validity of the assumptions of these two theories can be tested in terms of information acquisition. For example, it can be tested whether players are able to acquire all the relevant information necessary to form (accurate) beliefs about the expected actions of other players or to estimate the distribution of actions chosen by others.

Other bounded rationality models of strategic behavior, such as level-k (Stahl and Wilson 1994, 1995; Nagel 1995; Crawford 2003) and cognitive hierarchy (Ho et al. 1998; Camerer et al. 2004) explain out-of-equilibrium outcomes by assuming that individuals perform different and limited levels of iterative strategic thinking owing to limited cognitive capacities. For information acquisition, we may expect that agents do not play equilibrium because they fail to process relevant information. Hence, to test these theories we should verify whether players exhibit information search patterns that are consistent with their level-k.

A different picture is that proposed by the theories of social preferences. According to these theories, deviations from equilibrium are based on a different definition of decision utility. They reject the assumption that a person's behavior reflects only the maximization of his or her own utility and promote the relevance of competing motives such as altruism, reciprocity, and inequity aversion (Fehr and Camerer 2007).[8] To be supported by process data, theories of social preferences require that the information acquired by a player reflects his or her social motive. For example, a player motivated by fairness should look at the payoffs of others, regardless of whether these payoffs are strategically relevant or not.

Process Data and Backward Induction

Equilibrium predictions made by game-theoretic models of sequential bargaining are typically not supported by experimental results (Ochs and Roth 1989). In the literature, there are two possible explanations of this phenomenon: the first is that players deviate from equilibrium because of their limited cognition and the second is that players are inequity-averse or want to reciprocate cooperation. These two alternative hypotheses were tested by Camerer et al. (1993) and Johnson et al. (2002) by combining information-search patterns and choices. Johnson et al. (2002) used mouse-laboratory to study backward induction in three-stage Rubinstein bargaining games (Figure 3.7). In their study, participants were asked to acquire information about the pie size in different stages by clicking on the relative boxes.[9] Camerer et al. (1993) found that the offers ($2.11) were closer to the equal split ($2.50) than to the equilibrium prediction ($1.25). Their results could be explained by the inability of the players to find the equilibrium via backward induction, by inequality aversion (individuals dislike differences in final payoffs), or a combination of the two. Starting from the evidence that the equilibrium model in sequential bargaining did not account for the initial offers of the players, Camerer et al. (1993) used process data to understand whether some of the implicit assumptions of the equilibrium model were violated. For example, to compute a subgame perfect equilibrium offer players needed to open the second and the third boxes. If players did not open the third box they did not have enough information to compute an equilibrium offer. This simple line of reasoning suggested to Camerer et al. that deviation from equilibrium predictions could be related to how information was processed.



Source: Adapted from Johnson et al. (2002).

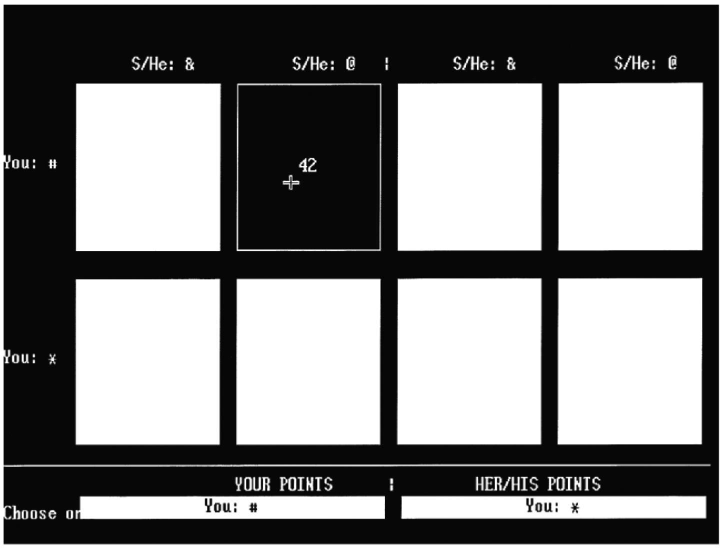
Figure 3.7 Mouse-laboratory screenshot of the three-stage bargaining game

In their analysis, Camerer et al. (1993) compared the information acquisition process of players who were trained to apply backward induction with that of untrained players. They found that trained players paid more attention to the second- and the third-round boxes, and made more transitions between them. Moreover, untrained players did not consider information following the same order as trained players. They mostly remained focused on the boxes related to the current round and did not pay sufficient attention to information about the subsequent rounds (for example, they did not open the second- and the third-round boxes 19 percent and 10 percent of the time, respectively). These results show that the search pattern of untrained players differs from the search pattern expected from players who apply backward induction.

To test whether players' behavior is better explained by limited cognition or inequity aversion, Johnson et al. (2002) classified players into different types, based on their search patterns, and tested whether there was correspondence between how players allocate attention and the decision rule adopted. Johnson et al. (2002) made the following predictions: they expected level-0 players to remain focused on the first-round boxes, ignoring future rounds; level-1 players to look one round ahead and open the second-round boxes; and equilibrium players to open the third-round boxes and allocate their attention mostly to the second- and third-round boxes. Johnson et al. (2002) found that the average offer for each type of player was close to that predicted by the level-k model. In particular, they found that the average offer of players classified as level-0 ($2.07) was significantly higher than that of players classified as level-1 ($1.71) and that the average offer of players classified as level-2 ($1.44) was significantly lower than that of players classified as level-1. Importantly, theories of social preferences could not explain these results because high offers were observed also when the counterpart was a robot player.

Process Data and Heterogeneity in Strategic Sophistication

Results obtained by Camerer et al. (1993) and Johnson et al. (2002) suggest that heterogeneity in search patterns leads to heterogeneity in players' choices. This link was also stressed in a mouse-laboratory experiment conducted by Costa-Gomes et al. (2001) to study strategic sophistication in one-shot normal form games (Figure 3.8). Costa-Gomes et al. (2001) tested the cognitive implications of alternative models of choice combining choice data and patterns of information search. To explain the behavior (choices and search patterns) of their players, they specified a priori nine possible types of players. Four of their types were non-strategic (or had diffused beliefs) since they did not require consideration of the incentives of the counterpart to predict their decisions. Five of their types were strategic and required both the formation of beliefs about the expected action of the counterpart and the correspondent best-response to them. Costa-Gomes et al. (2001) assumed that each type first decides which information search strategy to adopt, and then the information search strategy and the type both determine the final decision. To describe the link between the decision process and the choice, they associated each decision type with one (or more) search pattern(s). Despite finding heterogeneity in both players' behavior and lookup patterns, Costa-Gomes et al. (2001) observed that most of their participants exhibited lookups and choices consistent with the level-k model. They found that about two-thirds of their participants exhibited action choices and lookups patterns that were consistent with level-1 or level-2 models. The



Note: In this example, participants (the row players 'You') could see the payoffs one-by-one by left-clicking the mouse cursor in correspondence to the gray boxes. It was possible for the participant to have only one box open at a time. To open a new box or enter the decision, the participant had to close the open box by right-clicking the mouse cursor.

Source: Adapted from Costa-Gomes et al. (2001).

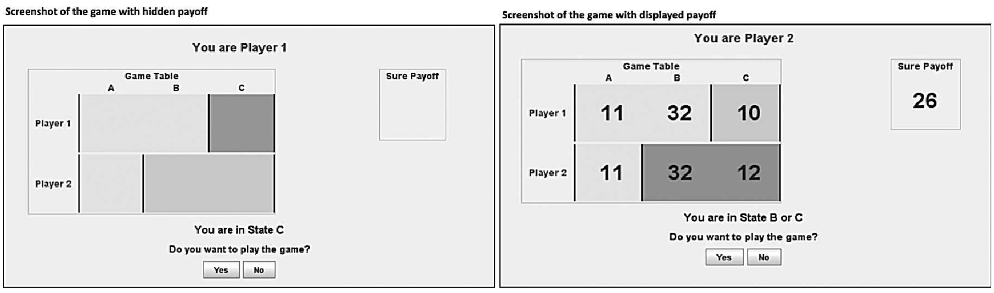
Figure 3.8 Mouse-laboratory screenshot of a two-by-two one-shot game dominance-1 model explained the behavior (choices and lookup patterns) of most of the remaining participants.[10]

Mouse-tracking was used also by Costa-Gomes and Crawford (2006) in a study where they elicited players' initial responses to a series of two-person guessing games. Similarly to Costa-Gomes et al. (2001), they identified different types of players using an econometric analysis and found that deviation from equilibrium could be predicted and explained assuming a hierarchy of boundedly rational types.

Process Data in Games with Private Information

Brocas et al. (2014) investigated the link between information search and decision strategy in games with private information. They used mouse laboratory to study strategic thinking in two-person betting games with three states and two-sided private information (Figure 3.9). They were interested in testing the predictions of two different classes of models. The first class includes models which predict that a player fully analyzes the game but makes imperfect inferences about the other player's action or believes that the counterpart made imperfect inferences about his or her own action (models of this type include the QRE, the CE and the analogy-based expectation equilibrium). The second class of models assumes that players sometimes have imperfect attention and ignore relevant information because of their bounded rationality (as in level-k and cognitive hierarchy theories).

Brocas et al. (2014) used a model-based clustering method to group participants according to their lookup patterns and choices. They found three clusters which approximately corresponded to level-3, level-2 and level-1 players, and a fourth cluster which included players who fully analyzed the game but made inferential mistakes. More generally, they found that deviations from Nash equilibrium were usually associated with failure to look at the relevant information and that the choices of the players could be predicted by the time they spent looking at relevant payoffs.



Note: The left-hand panel is a screenshot of the game as seen by the participants in the experiment. The right-hand panel is an example of the game with displayed payoff. The game included three possible states (A, B and C). The computer selected randomly one of the three states and each respondent privately observed a state partition (either one or two of the three states). For example, player 1 knew that the state was A or B or knew that the state was C for sure. Player 2 knew that the state was A for sure, or B or C. The respondent chose whether to bet or accept an outside option (sure payoff).

Figure 3.9 Example of the two-person betting games used by Brocas et al. (2014)

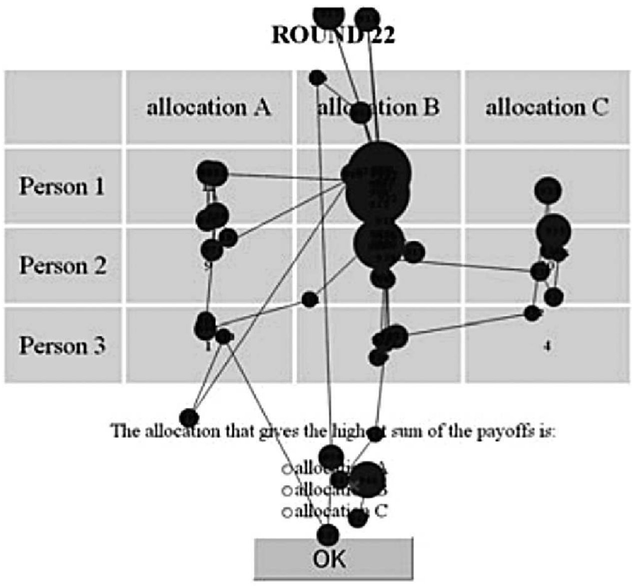
Process Data and Deception in Games

Process data were recorded to study deception in games. Wang et al. (2010) recorded eye-tracking and pupil dilation data in a sender–receiver game. The sender–receiver game represents a typical economic situation in which two players (the sender and the receiver) have different interests: the sender is incentivized to send a message to the receiver that exaggerates the truth, and the receiver is incentivized to infer correctly the true state from the message of the sender. However, there is evidence that the sender usually tells the truth more often than equilibrium predicts. Wang et al. argue that over-communication can be explained by a level-k model in which the behavior of a level-0 sender is anchored at the truth telling. In their analysis of eye movements, they showed that level-0 players (both senders and receivers) focused mainly on the payoffs corresponding to the true state. Conversely, the lookup patterns of level-1 and level-2 players were focused more on the payoffs corresponding to the true state plus a known bias parameter that depended on the level-type and the state-action combination. Wang et al. (2010) also investigated the underlying cognitive processes of over-communication by recording the senders' pupil dilation during the period in which they sent the message. They found that senders' pupils dilate when they sent messages that diverged from the true state and that the pupil dilation increased more when the deception had larger magnitude. These results show the predictive power of lookups and pupil dilation for inferring private state information.

Process Data and Social Preferences

The studies described up to now show how process data can be used to characterize players in terms of their ability to do different steps of iterative strategic thinking. Jiang et al. (2016) showed that, in certain strategic contexts, process data can also be used to characterize the social preferences of players. They started from the assumption that if an individual is motivated by a particular social preference, the way in which information is acquired should reveal that social preference. In their study, eye movements were recorded while participants played a simple three-person (dictator) distribution game. The choices in the game could be characterized according to three different types of social motives: efficiency (maximize the sum of the payoffs), maximin (maximize the minimum payoff) and envy (minimize the difference between the highest payoff of a player and the payoff of the dictator player). The participants performed a preference-based decision-making task in which they were free to adopt the decision strategy they prefer. Then, they performed a second task in which they were instructed and incentivized to choose according to each of the three possible decision rules (Figure 3.10). In the analysis, players were first classified according to their choices and then according to their information search patterns when making preference-based decisions. Patterns were characterized based on two types of variables: gaze time and saccades.

The first type of variable (gaze time) referred to the time spent looking at the payoffs of person one, two, and three. The second type (saccades) referred to the comparisons made by the respondent and included saccades within rows (eye movements between two allocations of the same person), saccades between rows (eye movements within the same allocation of two different persons) and saccades within areas of interest (eye movements that remained on the same payoff). Then, Jiang et al. (2016) used the patterns implemented



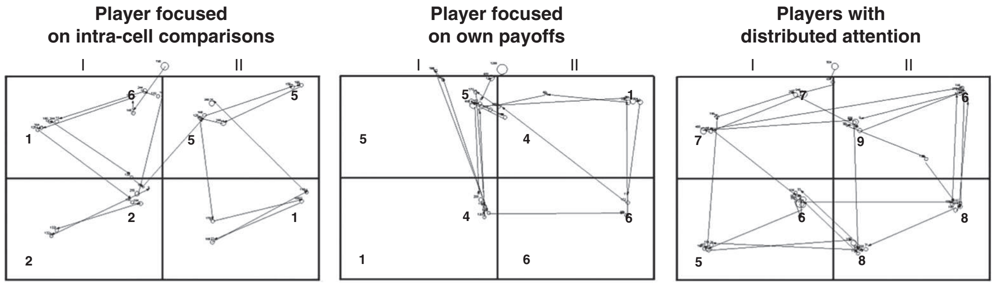
Note: The lines and circles depict saccades and fixations respectively. The diameter of the circles is proportional to the fixation duration.

Figure 3.10 Example adapted from Jiang et al. (2016) in which the respondent was instructed to choose according to one of three possible decision rules

by the participants while choosing according to the three decision rules as a template to predict the decision strategy adopted by the players when making preference-based decisions. Finally they compared the level of correspondence of the two classifications (one based on eye movements and the other based on choices). The results show that the classification based on eye movements leads to accurate predictions of players' choices, supporting the idea that choices are strictly related to the specific information search analysis adopted by the player.

Process Data and Subjective Levels of Strategic Sophistication and Social Preferences

In the studies described up to now, process data was used mostly to investigate separately strategic sophistication and social preferences, though it is likely that deviation from equilibrium can be owing to both aspects. In relation to this, the study of Polonio et al. (2015) started from the assumption that the strategy adopted by a player depends on two components: the player's level of sophistication and social motive. Following this theoretical framework, Polonio et al. (2015) conducted an eye-tracking study in which participants played two-person, two-by-two, one-shot normal form games. They tested whether the decision strategy implemented by the players could be described and predicted by the visual search patterns they used to acquire information about the game structure. To define the search patterns, Polonio et al. (2015) identified a subset of informative saccades that were considered useful for capturing pieces of information about the games. Informative saccades included: (1) saccades necessary to identify the presence of dominant actions; (2) identifying the action with the



Note: On the left-hand side is a player who compared his or her own payoffs with those of the counterpart within the four cells. In the middle, a player who remained focused on his or her own payoffs. On the right-hand side, a player with distributed attention who consider iteratively his or her own and his or her counterpart's payoffs. The lines indicate the saccades (that is, eye movements from one fixation to the next), and the circles the fixation location.

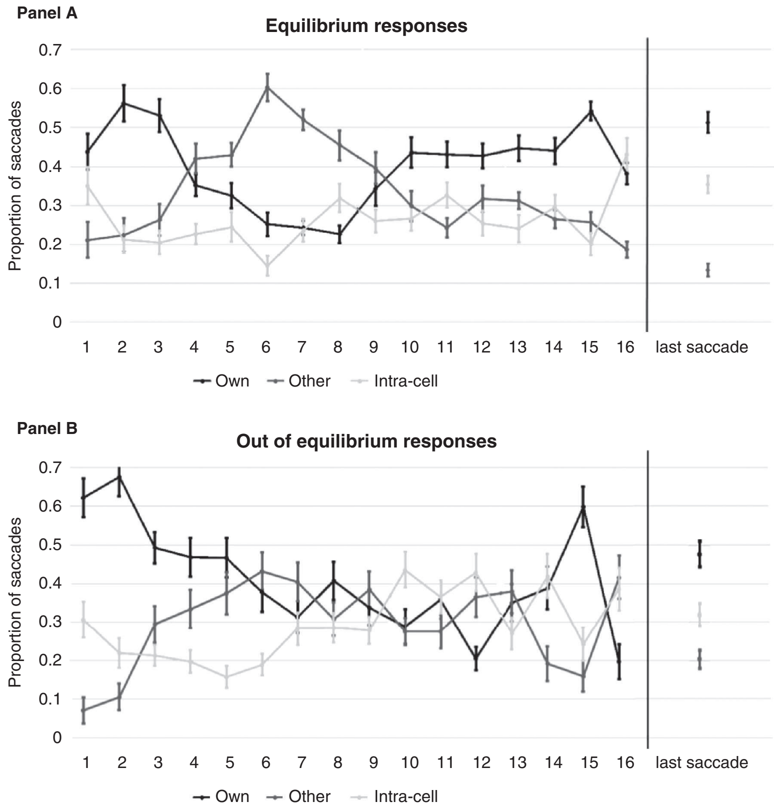
Source: Adapted from Polonio et al. (2015).

Figure 3.11 Eye-tracking data from three column players

highest average payoffs (for the player and the counterpart); and (iii) comparing the payoffs of the two players within the same cell.

Polonio et al. (2015) found that different groups of players used specific combinations of informative saccades in order to implement their decision strategies. They found two groups of participants who neglected information that was needed to best respond to the counterpart. In one group, participants simply compared their own payoffs with those of the counterpart within the four cells. In the other, participants focused their attention on their own payoffs. However, they also found a third group of participants who took into account the payoffs of the counterpart using an iterative step-by-step procedure. These participants looked first at their own payoffs, then at the payoffs of the counterpart, and then again at their own payoffs (Figure 3.11). Participants who compared their own payoffs with those of the counterpart were classified as cooperative or competitive players. Participants focused on their own payoffs were classified as level-1 players and participants with distributed attention as level-2 players. Using this classification based on visual search patterns, Polonio et al. (2015) were able to predict the choices of the four groups of players in games with different equilibrium structures. These results support the idea that players use stable decision strategies that can be identified with precision by looking at the information acquisition patterns. In a subsequent analysis, it was established that equilibrium choices in the two-by-two matrix games were made when the information acquisition followed a specific temporal pattern. According to the data, deviations from this specific temporal pattern led to out-of-equilibrium choices (Figure 3.12).

The results of Polonio et al. (2015) are supported by another eye-tracking study, conducted by Devetag et al. (2016). They showed that in two-person, three-by-three, one-shot games players adopt simplified strategies such as 'choosing the action with the highest average payoff' or 'the action leading to an attractive and symmetric payoff'.[11] They found that many players did not take into account the other players' incentives or considered the other player's payoffs only for a subset of game outcomes. The analysis of eye-movements emphasized the strong link between patterns of information acquisition used



Note: Panel A shows data for equilibrium choices. At the beginning of a trial, participants considered their own payoffs (first 4 saccades). Then, they looked at the other player's payoffs (saccades 4–9) and, finally, before making a decision, they looked again at own payoffs (saccades 10–16). Panel B shows the data for non-equilibrium choices. This demonstrates that in order to make an equilibrium choice a certain pattern of analysis should be followed.

Source: Adapted from Polonio et al. (2015).

Figure 3.12 The average proportions of saccades (across games) that occurred between player's own payoffs (own), between counterpart's payoffs (other) and between own and counterpart's payoffs (intra-cell) over time

by the players and the strategy adopted. They found that the lookup patterns of the players were heterogeneous but very stable.[12] Moreover, it was found that the prototypical visual search pattern adopted by each type of player is not affected by the type of game or by the presence of descriptive features (that is, 'features that can be changed without altering the game equilibrium properties'; Devetag 2016, abstract). Finally, it was found that one-third of the players chose according to focal payoffs and used information acquisition patterns that differ from those expected under the assumptions of the level-k model. The behavior of these players, as well as their visual search pattern, was similar to that of cooperative players identified in Polonio et al. (2015).

Process Data and the Analysis of Consistency between Choices and Beliefs in Games

In a similar experiment, Polonio and Coricelli (2019) used eye-tracking technique to identify possible causes of inconsistency between choices and beliefs in games. In their study, participants played a set of two player, three-by-three, one-shot games (choice task) and stated their beliefs about which action they expect their counterpart to play (beliefs elicitation task). Polonio and Coricelli (2019) classified participants into different types according to the pattern of visual analysis they used when playing the games and when stating their beliefs. Then, they tested for each type of player, the degree to which choices were consistent with stated beliefs. They found that participants classified as level-2 used a more sophisticated pattern of visual analysis when they were choosing their actions than when they were stating their beliefs, as if they were best responding to the belief that their counterpart was less sophisticated than themselves. This hypothesis was supported by the finding that their choices were highly consistent with their stated beliefs. Conversely, participants classified as level-1 or as having social preferences disregarded information which was necessary to find a best response to their stated beliefs. Polonio and Coricelli (2019) found that their choices and beliefs were generally inconsistent. They concluded that there are two main reasons why individuals do not best respond to their beliefs in games. Some individuals take into account the incentives of the counterpart when stating their beliefs, but not when choosing their actions (level-1 players). Others do not attempt to best respond to the expected action of the counterpart, but want to find a cooperative solution of the game (cooperative players). These findings have important implications for non-equilibrium models, such as level-k (Stahl and Wilson 1994, 1995; Nagel 1995) and cognitive hierarchy models (Camerer et al. 2004), since they show that individuals whose choices were consistent with the level-1 model did not assign equal probability to all counterparts' actions (as expected for level-0 players) but stated that the level-1 action is chosen much more frequently.

Process Data and Learning in Games

Process data can be useful also for testing different models of learning in games. Knoepfle et al. (2009) tested different learning theories assuming that each theory can be thought of as an information search algorithm that uses specific information about past actions and payoff to guide choices. In this instance, eye-tracking data are particularly useful since choices alone cannot clearly distinguish among alternative learning rules. Unfortunately, Knoepfle et al. (2009) did not find any learning rule that is supported by both choices and information search patterns. When they considered eye-tracking data, they found that players look more at information that is relevant for sophisticated models (in which players anticipate that their counterpart is learning) as compared to information that is relevant for adaptive models (in which players learn by generalized reinforcing). However, when they analyzed players' choices they found that adaptive models predict players' behavior more precisely than sophisticated models. They conclude that a learning model that can explain both choices and information acquisition data is still not present in the literature.

CONCLUSIONS

In this chapter, we described some research on process tracing in behavioral game theory. We provided some examples and some critical comments about the methodology in use. Experimentation in economics has reached a very high standard and a vast range of applications. Process tracing analysis represents a new frontier. We believe that process tracing approaches can contribute significantly to a better understanding of the cognitive and the emotional underpinnings of economic decision making, from how people evaluate the outcomes of their choices to how they form beliefs about what other people might do.

NOTES

*. The study was funded by the European Research Council (ERC Consolidator Grant 617629).
1. For example, if the action space is between 0 and 100, then equilibrium contribution is higher than 0 and less than 100.
2. Gill and Prowse (2017) find that fast decision makers are less efficient in games. However, they also report that overthinking can lead to bad choices.
3. A good example of this distinction is the evidence of social and anti-social punishment reported in Herrmann et al. (2008). In this study, Herrmann et al. (2008) find that in Western societies punishing free riders in repeated PG is prevalent, while in countries such as Saudi Arabia, Ukraine, Russia and Greece a non-negligible proportion of subjects use anti-social punishment to punish cooperators. This suggests that cooperators in these societies are seen as norm breakers.
4. This strand of literature is remarkably close in flavor to the unitary system view discussed previously. Rustichini (2008) argues that the resolution of the conflict between dual and unitary theories may lie in their synthesis.
5. Similar results were obtained by Suter and Hertwig (2011) who studied moral judgment: there were more deontological than consequentialist choices under time pressure, which in the strategic settings correspond to selfish and social behavior.
6. Velocity and acceleration are indexes of the degree of response competition at different time points (Hehman et al. 2015).
7. Quantal response equilibrium is also called the trembling-hand effect because people would make errors in the decision phase.
8. In some cases also competition and punishment.
9. Equilibrium predictions are typically rejected in this strategic setting.
10. Dominance-1 players assign equal probability to the opponent's undominated actions and zero probability to the remaining dominated ones.
11. The first strategy is expected of a level-1 player, whereas the second one is expected of a cooperative player.
12. The lookup pattern of each participant did not change much from trial to trial.

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