The Good, the Bad, and the Angry: An experimental study on the heterogeneity of people’s (dis)honest behavior

Hélène Barcelo¹ and Valerio Capraro²

¹Mathematical Science Research Institute, Berkeley, USA.  
²Middlesex University Business School, London, UK

Contact Author: V.Capraro@mdx.ac.uk

Abstract

We introduce a novel decision problem to experimentally study situations where people know that they can lie, but do not initially know the economic consequences: they have to invest time to find them out. We report numerous findings, the most intriguing of which is that, in our setting, people can be divided in three types: the Good, who act honestly independently of the corresponding payoff; the Bad, who maximize their payoff without even checking the payoff for telling the truth; the Angry, who first look at the payoff for telling the truth and then lie only if that is low.

Keywords: honesty, deception, lying, response time, time pressure
Introduction

The conflict between honesty and dishonesty is at the core of essentially all economic and social interactions. When people interact, they communicate, and when they communicate, they have the opportunity to misreport their private pieces of information. Dishonesty clearly has negative impact on government and companies. For example, every year, tax evasion costs about $100 billion to the U.S. government (Gravelle, 2009), and insurance fraud costs more than $40 billion to insurance companies.1

In the past decade, economists and psychologists have started studying (dis)honesty using incentivized economic problems (Erat & Gneezy, 2012; Fischbacher, & Föllmi-Heusi, 2013; Gneezy, 2005; Hurkens & Kartik, 2009; Kartik, 2009; Levine, & Schweitzer, 2014; Levine, & Schweitzer, 2015; Mazar, Amir, & Ariely, 2008; Shemereta & Shields, 2013; Weisel & Shalvi, 2015; Wiltermuth, 2011). For example, they have explored the effect on honesty of many exogenous and endogenous variables, such as: demographic characteristics (Abeler, Nosenzo & Raymond, 2016; Biziou-van-Pol et al., 2015; Cappelen et al., 2013; Capraro, 2017b; Childs, 2012; Dreber & Johannesson, 2008; Friesen & Gangadharan, 2012; Erat & Gneezy, 2012); social and moral preferences (Biziou-van-Pol, 2015; Levine & Schweitzer, 2014; Levine & Schweitzer, 2015; Shalvi & de Dreu, 2014); incentives (Dreber & Johannesson, 2008; Erat & Gneezy, 2012; Ezquerra, Rodriguez-Lara & Kolev, 2017; Fischbacher & Föllmi-Heusi, 2014; Gneezy, 2005; Gneezy, Kajackaitė & Soble, forthcoming; Kajackaitė & Gneezy, 2017; Mazar, Amir & Ariely, 2008); and cognitive mode (Andersen et al., 2018; Cappelen, Sørensen & Tungodden, 2013; Capraro, 2017a; Gino, Schweitzer, Mead & Ariely, 2011; Gunia et al., 2012; Konrad, Lohse, & Simon 2017; Shalvi et al., 2012).

While differing in important details, all these experiments share one common property: they are static, in the sense that they focus either on situations in which people are fully aware of the consequences of all available options, or on situations in which there is uncertainty about the consequences of the options, but this uncertainty cannot be cleared in any way. In these experiments there is no room for learning the consequences of the available actions. To be more precise, about half of the previous studies (e.g., Fischbacher & Föllmi-Heusi, 2013) implement a die-under-cup paradigm, in which participants roll a die privately (under a cup), and then are asked to report the outcome, knowing that they would be paid according to the reported number. Since participants know the outcome of the die and know the payoff function, they are fully aware of the consequences of all available actions. The other half (e.g., Gneezy, 2005), instead, implement a sender-receiver game, in which a person, named “sender”, is given a private information and is asked to report it to another person, the “receiver”, whose role is to guess the original piece of information given to the sender. The payoffs of both the sender and the receiver depend on whether the receiver guesses the original piece of information. Since the sender has no way to know whether the receiver is going to believe his message or not, the sender has no way to clear the uncertainty about the economic consequences of his available actions. (There are also studies implementing a sender-receiver game in which the receiver makes no choice (e.g., Biziou

---

1See https://www.fbi.gov/stats-services/publications/insurance-fraud/insurance_fraud
van Pol et al, 2015; Capraro, 2017a). In this case, there is no uncertainty at all and, consequently, these studies belong to the class of studies in which subjects are fully aware of the consequences of the available actions).

Thus, although important, these studies provide an incomplete picture as, in reality, people oftentimes make decisions within a dynamic setting in which they know that they will have a chance to lie or to tell the truth, but they do not initially know the exact material consequences of these actions. And they have to invest resources (e.g., time) to find them out.

Such situations are very common both in economic and in social interactions. For example, suppose that John owns a car, which he would like to sell to a private person. John wants to maximize his profit, so he is tempted to stretch the truth about the car. Thus, before meeting with a potential buyer, John knows that he will have a chance to misreport some information. For example, in case the potential buyer asks him about the last time he replaced an important part of the car (e.g., the brakes, or the clutch), John may say that it happened more recently than it actually did, so as to show that that part is newer (and more valuable) than it actually is. However, before meeting with the potential buyer, John does not know how convenient stretching the truth is. For instance, it might happen that the potential buyer comes to the meeting accompanied by a friend, who happens to be a car expert, who would easily find out whether John is lying about the true state of the car.

In this work, we capture the essence of this type of interactions by means of a novel decision problem, in which participants, after being informed that they will have a chance to report a piece of information either truthfully or by stretching it (several different ways to stretch the truth will be available), and before actually choosing how to report that piece of information, need to invest time to explore the payoffs associated to the available strategies.

This design turns out to be particularly interesting also because it opens the way to a completely new set of research questions. Indeed, most previous studies on deception implement either binary decision problems – in which subjects get to choose between two strategies, one corresponding to telling the truth and one corresponding to lying (Biziou van Pol et al., 2015; Capraro, 2017a; Gunia et al., 2012) – or decision problems in which there are many different ways to lie, but finding which lie maximizes the payoff is trivial (Cappelen et al., 2013; Erat and Gneezy, 2012; Gneezy, 2005; Shalvi et al., 2012; Fischbacher, & Föllmi-Heusi, 2013; Sheremeta and Shields, 2013). On the contrary, in our case, subjects can lie in several different ways: they can explore all potential payoffs and then report the piece of information that corresponds to the global maximum; or they can explore only some payoffs and then report a piece of information that corresponds to an early local maximum (a local maximum that can be found easily and quickly – to be properly defined later); or they can explore the payoff corresponding to reporting the truth and then decide to lie only if this payoff is low (in case they decide to lie, they can do it in at least two ways: they can choose the global maximum or they can look around the truth for a local maximum); subjects can even be indifferent and pick one choice at random. Thus, by looking at the distribution of choices, we can divide people in types according to the strategy they implement and thus we can describe people’s decision-making process in lying contexts in a much more refined way than previously done.
One important tool for studying heterogeneity in people’s decision making will be the analysis of people’s response time. This will allow us to answer questions about what people do with their time. For example: do people just look at the payoffs and then decide, or is there a substantial proportion of people who do not even look at the payoffs? How do these people behave?

Apart from helping us exploring heterogeneity in people’s (dis)honesty, measuring response time will also allow us to answer questions regarding the correlation between response time and honesty, that were left open by previous studies. Previous work has investigated only the effect of response time on honesty in situations in which lying is not incentivized (Spence et al., 2001; Walczyk et al., 2003). These works found that dishonesty takes longer than honesty. With our design, we can go beyond these studies, by looking at the relation between response time and dishonesty when lying is incentivized. This is not a trivial extension: as Shalvi et al (2013) pointed out, monetary incentives can, in principle, revert the correlation between response time and honesty.

Finally, we will also use our design to explore the effect of time pressure on people’s decisions. Previous studies have explored the effect of time pressure on the overall level of honesty (Gunia et al., 2012; Capraro, 2017a; Konrad et al., 2017; Shalvi et al., 2012). With our design, we can explore also the effect of time pressure on the distribution of choices. This is an important application, because the role of time pressure and, more generally, the role of intuition on honesty has been at the center of the debate in the last years (Andersen et al., 2018; Cappelen, Sørensen & Tungodden, 2013; Capraro, 2017a; Debe, Verschuere, & Crombez, 2012; Gino et al., 2011; Gunia et al., 2012; Konrad et al., 2017; Mead et al., 2009; Shalvi et al., 2012; Spence et al., 2001; van’t Veer, Stel & van Beest, 2014; Walczyk et al., 2003), as a part of the more general research program of classifying prosocial behaviors according to whether they are intuitive or reflective (Capraro and Cococcioni, 2015; Capraro and Cococcioni, 2016; Capraro et al., 2016; Corgnet et al., 2015; Duffy and Smith, 2014; Krajbich et al., 2015; Lotz, 2015; Rand et al., 2012; Rand et al., 2014; Rand, 2016; Rand et al., 2016). This research program is receiving considerable attention because comprehending which behaviors are intuitive and which are reflective “has major implications for understanding human nature, and from a practical point of view for designing institutions to encourage or discourage certain behaviours” (Krajbich et al., 2015). Thus, with our design we can contribute also to this literature by addressing not only the question whether time pressure affects honesty, as it has been done in previous studies (Gunia et al., 2012; Capraro, 2017a; Konrad et al., 2017; Shalvi et al., 2012), but also the more general question whether time pressure affects the dynamic of reasoning.

With this plan in mind, we conducted a 2x2 experiment in which we manipulated response time (time pressure vs no time constraint) and the payoff corresponding to telling the truth (low vs high) as detailed below.

**Experimental design and procedure**

We conducted an experiment on the online platform Amazon Mechanical Turk (AMT). AMT experiments are easy and cheap because subjects participate from their homes by simply completing an online incentivized survey that takes no more than a few minutes. This allows researchers to significantly decrease the stakes of the experiment, without compromising the
results. Several studies have indeed shown that data gathered using AMT are of no less quality than data gathered using the standard physical lab (Paolacci, Chandler, & Ipeirotis, 2010; Horton, Rand, Zeckhauser, 2011; Mason & Suri, 2012; Berinsky, Uber & Lenz, 2012; Goodman, Cryder, & Cheema, 2013; Paolacci & Chandler, 2014). Moreover, as an upside with respect to standard laboratory experiments, AMT experiments use samples that are more heterogeneous than the standard laboratory experiments, that are typically conducted using a pool of students.

After entering their Turk ID, subjects were told that they will generate two pieces of information:

- A position, which will be a number, for example 14.
- A list of potential payoffs between 1 and 90 cents, such as: 23, 73, 34, 22, 2, 11, 54, 21, 44, 3, 22, 6, 89, 45, 67, 23, 65, 46, 77, 1, 86, 5, 4.

They were told that their payoff would be equal to the number in the given position. Thus, in this case, it would be 45c, because 45 is in position 14. (We chose this particular example, because the payoff is essentially equal to the expected payoff from a random sequence, which is 45.5c. We did not want to prime subjects towards being lucky or unlucky).

Then we told participants that their job was to report the position they generated. We made it clear that the survey was anonymous and that we did not know the position they generated. Thus participants knew that they could report also a different position than the one they generated.

After these general instructions, participants answered six comprehension questions with mock positions and mock lists. The positions and the lengths of the mock lists were all different, in order to avoid that participants get used to find the payoff associated with telling the truth without actually counting, and to avoid that subjects get used to count backwards. Only participants who answered correctly all questions were allowed to proceed to the real experiment. Comprehension questions included questions about payoff maximization. So, participants who passed this attention test were aware of the fact that they could increase their payoff by misreporting the position they generated.

After the comprehension questions, subjects were told that the real experiment was about to start, that they would generate a position and a list of potential bonuses, and that their payoff for the survey would be equal to the number in the position they report. Then we asked them to press the next button to start playing.

In the next screen, participants were randomly divided in two treatments. In the Lucky condition, they were communicated that the position they generated was 22; in the Unlucky condition, they were communicated that the position they generated was 19. (The reason why the first condition is called Lucky while the second one is called Unlucky will be clear in the next paragraph). Participants were asked to take note of this position on a piece of paper, and then to press the next button to generate the list of potential bonuses.

In the following screen, all participants were shown the same list of potential bonuses (i.e., 25, 3, 63, 54, 28, 70, 37, 36, 26, 31, 43, 15, 30, 60, 33, 37, 15, 63, 16, 50, 4, 71, 79, 2, 85, 48) and they
were asked to report the position they generated, either under Time Pressure (within 15 seconds) or with No Time Constraint. In both the Time Pressure and the No Time Constraint conditions, we took a measure of response time using a timer. (In the No Time Constraint condition the timer was not visible to participants). Thus, in this work response time is defined as the sum between the time spent exploring the payoffs and the time needed to make a decision and type it.

Before moving on, we make two observations about the list of potential payoffs. First, if participants in the Unlucky condition report the true position, then they get only 16c (because 16 is in position 19); if participants in the Lucky condition report the true position, then they get 71c (because 71 is in position 22), which is close to the maximum one can get, which is 85c. Second, both Position 19 and Position 22 (the true positions) are adjacent to positions with a greater payoff. Thus, both lucky and unlucky participants can stretch the truth and get a greater payoff very easily (unlucky participants can increase their payoff by reporting Position 18 or Position 20, instead of their true position; similarly, lucky participants can increase their payoff very easily by reporting Position 23, instead of their true position). In other words: telling the truth after checking its associated payoff is essentially as easy as stretching the truth after checking its associated payoff. This property is crucial in order to avoid that subjects prefer one choice over the other one only because that is easier. And this is also the main reason that made us prefer this experimental design over apparently easier ones. For example, an alternative experimental design would be to present the payoffs “hidden”, so that subjects cannot initially see them, and let subjects uncover the payoffs sequentially, and then analyze the way they uncover them. An important limitation of this alternative is, indeed, that people who would lie only if their payoff is small are incentivized to tell the truth because in order to lie they must uncover more (and potentially many more) payoffs. To avoid this confound, we opted for the current design.

After reporting the position, subjects were asked standard demographic questions (sex, age, education) and then they were given the “completion code” needed to submit the survey to AMT and claim for the payment.

We refer to the Appendix for full experimental instructions.

Results

Participants

We conducted two sessions. In the first session, we recruited 600 participants located in the US, 200 in the Time Pressure condition, 200 in the No Time Constraint condition, and 200 in a Time Delay condition (participants were asked to think carefully for at least two minutes before making their choice). Given the replicability crisis in social sciences (Open Science Collaboration, 2015), we decided to conduct a second session with the goal of replicating our main results. However, since the results in the Time Delay condition were identical to those in the No Time Constraint condition, in the second session, we decided to focus only on the Time Pressure and No Time Constraint conditions. Thus we recruited 400 more participants, two-hundred per condition, again located in the US. Results of the second session were essentially the same as those of the first session. Thus, we analyze all 800 observations together (400 in the Time Pressure condition and 400 in the No Time Delay condition). After eliminating multiple
observations and subjects who submitted the survey without completing it, we are left with 704 observations (mean age = 36.8, females = 47.9%).

**Distribution of reported positions**

Figure 1 reports the histogram of the reported positions (all 704 observations together). Note that Position 19 and Position 22 correspond to the true positions in the Unlucky and Lucky conditions, respectively. The overall rate of honesty is 83%, which is in line with previous studies exploring dishonest behavior in similar situations (i.e., using die-under-cup-like paradigm, in which deceiving has no consequences on other participants). For example, Fischbacher and Föllmi-Heusi (2013) report a distribution of responses that is consistent with an overall rate of honesty of 70%; Shalvi et al. (2012) report a distribution of responses that is consistent with an overall rate of honesty of 85%; Gneezy et al (forthcoming) who, contrarily to the formerly mentioned studies, observed individual choices, report, in three treatments, an overall rate of honesty of 74%, 73% and 67%, respectively. Before analyzing the choices made by the liars, we observe that Position 25 is the one corresponding to the global maximum, while Position 3, Position 6, Position 18, and Position 23 correspond to the local maxima. It follows that virtually all liars maximized their payoff (either locally or globally). There is very little evidence of people playing other strategies, such as a random strategy (12 subjects out of 704).

**Result 1.** Virtually no one is indifferent, that is, virtually all participants either report the true position or report a position which corresponds to a local (or a global) maximum.

Moreover, among the 118 liars, only 10 chose to “stretch the truth” by choosing a position adjacent to the true position. In other words, 108 out of 118 liars (91.5%), either reported the position corresponding to the global maximum, or reported a position corresponding to an *early local maximum*, where early local maximum stands for positions 3 and 6.

**Result 2.** Very few people (8.5% of those who lie) “stretch the truth”, that is, in our sample, more than 90% of those who lie, either report the piece of information corresponding to the global maximum, or report a piece of information corresponding to an early local maximum: very few people choose a local maximum near the truth.

A similar result was obtained recently by Gneezy et al (forthcoming) in the context of static interactions. In three treatments, they found that 91%, 80% and 68% of the liars, lie maximally.

**Replication 1.** Most liars lie maximally (Gneezy et al, forthcoming).
Heterogeneity in people’s dishonest behavior

We now restrict the analysis to the No Time Constraint condition (N = 347, honesty = 84.2%, dishonesty = 13.8%), and we explore heterogeneity in people’s behavior in “natural” conditions. We postpone the exploration of the effect of time pressure to the last subsection of this section. Thus, in this and the following subsections, unless explicitly stated, all analyses are referred to the class of subjects in the No Time Constraint condition.

Our first observation is that all 12 “indifferent” participants reported above were in the Time Pressure condition. In other words, in the No Time Constraint condition, all participants are either honest or purposely dishonest: they report a position corresponding to a local or a global maximum of the payoff function. We start by looking at heterogeneity in people’s dishonest behavior. One interesting question is whether people who decide to lie, do so in advance and thus do not even look at the payoff associated with reporting the truth (Unconditionally Payoff Maximizers, “Bad” people), or whether they first look at their true payoff and then lie only if this payoff is low (Relatively Honest, “Angry” people).

To answer this question, we note that if all liars were Unconditionally Payoff Maximizers, then being unlucky versus lucky would have no effect on honesty. Thus, to show that a significant
proportion of liars come from Relatively Honest people, it is enough to show that being lucky
has an effect on honesty. To this end, we run logistic regression predicting honesty as a function
of a dummy variable, named “lucky”, which takes value 1 if a subject participated in the Lucky
condition, and 0 otherwise. We find that Lucky participants were more honest than Unlucky
participants (77.6% vs 91.4%, without control on sex, age, and education: coeff = 1.12, z = 3.41,
p < .001; with control: coeff = 1.14, z = 3.38, p < .001). These demonstrates that a significant
proportion of liars are Relatively Honest.

**Result 3.** A significant proportion of liars are Relatively Honest, that is, they do not decide to lie
in advance: they first invest resources to look at the payoff corresponding to being honest, and
then lie only if this payoff is low.

A special corollary of this analysis is that Unlucky subjects lie more than Lucky subjects, a result
that was already found by Gneezy et al. (2013) and Gneezy et al. (forthcoming).

**Replication 2.** Unlucky subjects lie more than lucky subjects (Gneezy et al., 2013; Gneezy et al.,
forthcoming).

*The effect of response time*

Before exploring heterogeneity in people’s *honest* behavior, we make an intermediate step and
we study the effect of response time on honesty.

In order to take into account for a distribution of response times that is highly right skewed, we
log-transform response time (Rand et al., 2012; Rand et al., 2014; Capraro, 2017a). Logistic
regression predicting the probability of telling the truth as a function of (log of) response time
shows that, overall (Lucky and Unlucky conditions together), there is a clear negative effect of
reaction time on honesty (without control on sex, age and education: coeff = -1.12, z = -7.15, p < .001;
with control: coeff = -1.25, z = -7.24, p < .001). Importantly, this effect retains significance
when we control for the reported position (without control on sex, age, education: coeff = -1.21,
z = -4.66, p < .001; with control: coeff = -1.31, z = -4.78, p < .001). This robustness check is
important, because, otherwise, one may argue that dishonest behavior takes longer just because
subjects need to explore more payoffs. This robustness check shows that this is not the case.
Additionally, the negative effect of response time on honesty retains significance also when we
split the sample in the Unlucky condition (without control on sex, age, education: coeff = -1.81, z
= -6.85, p < 0.001; with control: coeff = -1.89, z = -6.74, p < 0.001), and the Lucky condition
(without control on sex, age, education: coeff = -0.79, z = -3.09, p = 0.002; with control: coeff = -
0.82, z = -3.15, p = 0.002). Moreover, there is an interaction between (log of) response time and
the “lucky” dummy variable (without control: coeff = 1.02, z = 2.79, p = 0.005; with control:
coeff = .98, z = 2.61, p = 0.009). This suggests that the effect of response time, although present
in both the Lucky and the Unlucky conditions, was stronger in the Unlucky condition.

**Result 4.** There is a negative correlation between response time and honesty. This negative
correlation is significant for both Lucky and Unlucky participants, but it is stronger among
Unlucky participants.

*Heterogeneity in people’s honest behavior*
We have seen that, in our setting, most people are honest, and that some of the honest people are Relatively Honest, that is, they first look at the exact payoff corresponding to telling the truth, and then decide whether to lie or to tell the truth. One interesting question is whether all honest participants are Relatively Honest or there is a class of Maximally Honest participants (“Good” people) who report the true position independently of the exact payoff corresponding to telling the truth (The terminology Maximally Honest was already introduced by Fischbacher & Föllmi-Heusi (2013) to describe a very similar class of subjects, those who, knowing the payoff corresponding to telling the truth, tell the truth even if, doing so, they get the minimum available payoff).

To answer this question, we first observe that if all people were Relatively Honest, then the difference in honest behavior between lucky and unlucky participants would be observable also in subsamples of the full sample. In particular, it would be observable among Fast participants, that we define as those who took less than the median response time to make a decision (median response time = 11 seconds). However, this is not the case: Fast participants in the Lucky condition behaved essentially the same as the Fast participants in the Unlucky condition, and they were extremely honest (rate of honesty: 98.8% vs 96.7%; logit regression without control: coeff = 1.02, z = 0.87, p = 0.383; with control: coeff = 1.14, z = 0.96, p = 0.335). See Figure 2. This shows that Fast participants are virtually all Maximally Honest, who decide to act honestly independently of the exact payoff associated with telling the truth. Of course, we cannot conclude that they are all Maximally Honest. Some of the Fast participants did certainly look at the payoff corresponding to telling the truth and chose conditionally to it, but they were not enough to generate a significant difference in honesty between lucky and unlucky participants. Similarly, among the Slow participants (those who took longer than 11 seconds to decide), there were certainly some Maximally Honest people, but, since Slow and Unlucky participants were way more dishonest than Slow and Lucky ones (rate of honesty: 58.7% vs 84.1%; logit regression without control: coeff = 1.32, z = 3.57, p < .001; with control: coeff 1.30, z = 3.33, p = 0.001), we can say that a significant proportion of Slow participants are Relatively Honest. Summarizing, while at this stage of the research it is impossible to estimate the exact proportions of Relatively versus Maximally Honest participants, we can logically conclude that the vast majority of subjects (84.2% in our setting, because this is the rate of honesty in the No Time Constraint condition) are either Maximally or Relatively Honest (as opposed to being for example Unconditionally Payoff Maximizers, or Indifferent), and that both of these classes are significant.

Additionally, among the 15.8% subjects who lie in the No Time Constraint condition, we find that all of them report either a local maximum or a global maximum. This allows us to conclude that the proportion of Unconditionally Payoff Maximizers (Bad people, subjects with a zero cost of lying, who aim straight at maximizing their payoff without even looking at the payoff for telling the truth) is bounded above by 15.8%, that is, the upper bound for the proportion of the Unconditionally Payoff Maximizers is equal to the percentage of all liars. The true percentage of Unconditionally Payoff Maximizers is likely to be smaller, because a substantial proportion of liars are not Unconditionally Payoff Maximizers, but comes from Relatively Honest subjects who were unhappy with the payoff corresponding to telling the truth, and so decided to lie. However, since we do not know the proportion of Relatively Honest subjects, we cannot deduce
the true percentage of Unconditionally Payoff Maximizers subjects. In principle, all liars could actually be Relatively Honest. Is the class of Unconditionally Payoff Maximizers non-empty, i.e., are there liars that are not Relatively Honest? Yes, because there are participants choosing early local maxima. Although they are very few (5 out of 356 participants), they show that there are at least some participants who do not care about finding out the payoff corresponding to telling the truth: they aim straight at maximizing their payoff (while saving time).

We can now summarize these observations with the following results.

**Result 5.** The vast majority of participants (bounded below by 84%) are either Maximally Honest (they tell the truth independently of the payoff corresponding to telling the truth), or Relatively Honest (they first look at the payoff corresponding to telling the truth, and then they lie only if this payoff is low). Both these classes are substantial. Only a small (but non-null) proportion of subjects (bounded above by 16%) are Unconditionally Payoff Maximizer (they report a piece of information corresponding to a local or a global maximum without even looking at the payoff associated with telling the truth). No one play other strategies.

![Figure 2](image.png)

*Figure 2.* Rate of honesty among subjects in the No Time Constraint condition, split by whether they were lucky or unlucky and by response time (faster half vs slower half).

*The effect of time pressure on honesty*
Next we analyze the effect of time pressure on honesty. A manipulation check confirms that subjects under time pressure took much shorter to make a decision than subjects who decided with no time constraint (13.8s vs 24.4s, ranksum: p < .001).

Overall, we find that the rate of honesty under time pressure is not statistically different than the rate of honesty without time constraint (82.3% vs 84.1%; without control: coeff = -0.123, z = -0.64, p = 0.524; with control: coeff = -0.156, z = -0.78, p = 0.437). This remains true when we split the sample in the Lucky versus Unlucky condition (lucky: 85.9% vs 91.4%; without control: coeff = 0.567, z = -1.60, p = 0.109; with control: coeff = -.560, Z = -1.58, p = 0.115; unlucky: 78.9% vs 77.6%; without control: coeff = 0.076, z = 0.30, p = 0.765; with control: coeff = .0632609, z = 0.24, p = 0.808).

However, we find that time pressure has the effect of changing the distribution of positions (Kolmogorov-Smirnov, p = 0.038). Where does this effect come from, if the overall rate of honesty is constant across time manipulation conditions? In what follows, we argue that time pressure has the effect of: (i) transforming would-be Global Maximizers into Local Maximizers, and (ii) generating a small proportion of confused subjects. This is very clear from Table 1, which compares the distribution of choices in the Time Pressure condition with that in the No Time Constraint condition. Table 1 indeed highlights that the number of honest choices is essentially the same in the Time Pressure and in the No Time Constraint (294 vs 291), so are essentially the same the people stretching the truth (5 people in each condition). The only difference between the Time Pressure condition and the No Time Constraint condition is given by: (i) many of the people who would choose the global maximum in the No Time Constraint condition end up choosing an early local maximum in the Time Pressure condition; (ii) twelve participants are not classifiable, probably due to confusion.

|                                | Time Pressure | No Time Constraint |
|--------------------------------|---------------|-------------------|
| # honest                       | 294           | 291               |
| # choosing global max          | 12            | 43                |
| # choosing early local max     | 34            | 5                 |
| # stretching the truth         | 5             | 5                 |
| # not classifiable in one of the above | 12          | 0                 |

*Table 1.* Distributions of the reported positions in the Time Pressure and in the No Time Constraint conditions.

**Result 6.** Time pressure has no effect on the rate of honesty, but it does have an effect on the distribution of reported positions: (i) it transforms would-be global maximizers into local maximizers, and (ii) it generates a small proportion of confused subjects.

**Gender effect**

We conclude by exploring the effect of gender on honesty. Overall, in our design, women were more honest than men (without control on age and education: coeff = .597, z = 2.87, p = 0.004; with control on age and education: coeff = .580, z = 2.78, p = 0.005). This result is in line with the meta-analysis by Capraro (2017b).
Replication 3. Men lie more than women (Dreber & Johannesson, 2008; Capraro, 2017b).

Discussion

We analyzed dishonesty in dynamic contexts by means of a novel decision problem. Dynamic means that, in our experiment, people know that they will have a chance to lie, but they do not initially know the payoffs associated to each available action. They only know that it is between 1 cent and 90 cents, and they need to invest time to find out the exact payoff associated with telling the truth, as well as to find the maximum possible payoff. Moreover, we built the decision problem in such a way that, during the payoff search, people find also some local maxima. This design thus opens the way to a number of questions that were not addressed in previous studies. What is the distribution of choice? Do people invest time to find out the payoffs? What strategy do people who do not care about finding out the payoffs play? Do liars decide to lie only after looking at their true payoff or do they decide to lie in advance and do not even care about finding out their true payoff?

We found a number of results which, to the best of our knowledge, are new in the literature. Our main result is that, in our setting, subjects make choices following different paths: a significant proportion (around 50%, i.e., the percentage of Fast subjects) of subjects are Maximally Honest (the “good”), that is, they act honestly independently of the exact payoff corresponding to telling the truth. A small, but non-null, proportion (upper bound = 16%) of Unconditionally Payoff Maximizers (the “bad”), who aim at maximize their payoff (globally or locally, depending on the amount of time the decide to spend searching for payoffs). All the remaining subjects are Relatively Honest (the “angry”), that is, they invest time to find out the payoff associated with telling the truth, and then lie only if this payoff is low. No one play other strategies.

These results can also be interpreted in terms of cost of lying. Previous studies have shown that some people act honestly even when they have a chance to tell a Pareto white lie, which would benefit all parties involved by minimizing, at the same time, social inequalities (Biziou van Pol, et al., 2015; Cappelen, et al., 2013; Erat & Gneezy, 2012). In this case, honest behavior cannot be explained in terms of social preferences (Charness & Rabin, 2002; Fehr & Schmidt, 1999) and thus these results have been taken as evidence that some subjects have an intrinsic cost of lying. However, little is known about the distribution of the cost of lying. Our findings provide an upper bound of 16% for the class of subjects with a zero cost of lying (who correspond to Unconditionally Payoff Maximizers), and thus show that most subjects (bounded below by 84%) have a non-zero cost of lying. Moreover, we found that about 50% have a relatively high cost of lying, as they tell the truth independently of the payoff corresponding to telling the truth (Maximally Honest).

A similar classification was obtained by Fischbacher & Föllmi-Heusi (2013) using the die-under-cup paradigm. Analyzing the proportion of subjects who reported the outcome 1 – which minimizes their payoff – they concluded that at least 39% of the subjects have a high cost of lying as they act honestly, even if that means getting the lowest available payoff. Similarly, they found an upper bound of 22% for the proportion of participants with zero cost of lying, who aim
at maximizing their payoff. In a similar experiment, Gneezy et al. (forthcoming) found that 55% of the participants act honestly, even if that means getting the lowest available payoff. It is refreshing that these estimations are reasonably close to ours (50% for the class of Maximally Honest participants and 16% for the class of Unconditionally Payoff Maximizers). However, although similar, our classification is finer along one important dimension. In the experiments by Fischbacher & Föllmi-Heusi (2013) and Gneezy et al (forthcoming), subjects knew the payoff corresponding to telling the truth, and thus one cannot conclude anything about the cognitive process bringing to the decision. For example, it is possible that honest participants correspond to those with very high self-control, who first look at the payoff corresponding to telling the truth, then have an impulse to lie, which they then override thanks to their self-control. On the contrary, our data suggest that there is a large proportion of participants (that we estimated to be about 50%) who do not even look at the exact payoff corresponding to telling the truth, as they are extremely fast to respond. Thus, honesty among these participants does not seem to come from a deliberate act devoted to restrict an impulse. It looks rather the fast, automatic, intuitive response. Connecting to the debate about whether honesty is deliberative or intuitive (Capraro, 2017a; Gunia et al., 2012; Konrad et al, forthcoming; Shalvi et al., 2012), our results show that, at least for a large proportion of subjects, honesty is the automatic response.

Subsequently, we looked at the effect of response time on honesty. To the best of our knowledge, only two studies have looked at the effect of response time on honesty (Spence et al., 2001; Walczyk et al., 2003) and found that dishonest answers require more time. However, both these studies have analyzed situations in which people were not incentivized to lie. This led Shalvi et al. (2013) to argue that in incentivized experiments the correlation can even reverse, as people are motivated to lie. Our results show that, at least in our case, this does not happen: dishonesty takes longer even when people are motivated to lie.

Finally, we looked at the effect of time pressure on honesty. Previous research, using static settings, has led to mixed results, with some studies finding that time pressure increases dishonesty (Gunia et al., 2012; Shalvi et al., 2012), yet others finding that time pressure increases honesty (Capraro, 2017a; Konrad et al, forthcoming). In our dynamic setting, we find that time pressure has no effect on honesty, but it does have an effect on the distribution of responses. Precisely: time pressure (i) transforms would-be global maximizers into local maximizers, and (ii) generates a small proportion of confused subjects.

As side results, we show that three important results of previous literature extend from the static setting where they were first found, to our dynamic setting: the result by Gneezy et al (2013) that unlucky people lie more than lucky people; the result by Gneezy et al (forthcoming) that most liars lie maximally; and the result that men lie more than women in self-serving situations. Especially the latter result is somewhat interesting and non-trivial. An earlier paper by Dreber and Johannesson (2008) showed that men lie more than women. This result was then replicated by Friesen and Gangadharan (2012), but not by Child (2012). Erat and Gneezy (2012) found that the effect of gender on lying may depend on the consequences of lying: in their setting, men lied more than women when lying benefits all parties involved (Pareto white lies), but women lie more than men, when lying benefits another person at the cost of the liar (altruistic white lies). However, this result was not replicated by Biziou van Pol et al. (2015), who, in a similar setting, found that men tell more altruistic white lies than women and that there is no gender difference
in telling Pareto white lies. Two recent meta-analysis shed light on these questions. Abeler, Nosenzo and Raymond (2016) found that men lie more than women in general. But they do not distinguish across different types of lie. Capraro (2017b) found that men lie more than women across each different type of lie. Thus, in particular, men lie more than women in self-serving situations. Our current results add to this literature by confirming that men lie more than women in self-serving situations also in dynamic settings.
References

1. Abeler, J., Nosenzo, D., & Raymond, C. (2016). Preferences for truth-telling. CEDEX Discussion Paper No. 2016-13.
2. Andersen, S., Gneezy, U., Kajackaite, A., & Marx, J. (2018). Allowing for reflection time does not change behavior in dictator and cheating games. Journal of Economic Behavior and Organization, 145, 24-33.
3. Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon.com’s Mechanical Turk. Political Analysis, 20, 351-368.
4. Biziou-van-Pol, L., Haenen, J., Novaro, A., Liberman-Occhipinti, A., Capraro, V. (2015). Does telling white lies signal pro-social preferences? Judgment and Decision Making, 10, 538-548.
5. Cappelen, A. W. Sørensen, E. Ø., & Tungodden, B. (2013). When do we lie? Journal of Economic Behavior and Organization, 93, 258-265.
6. Capraro, V., & Cococcioni, G. (2015). Social setting, intuition, and experience in laboratory experiments interact to shape cooperative decision-making. Proceedings of the Royal Society B: Biological Sciences, 282, 20150237.
7. Capraro, V., Cococcioni, G. (2016). Rethinking spontaneous giving: Extreme time pressure and ego-depletion favor self-regarding reactions. Scientific Reports, 6, 27219.
8. Capraro, V., Corgnet, B., Espín, A. M., Hernán-González, R. (2017). Deliberation favours social efficiency by making people disregards their relative shares: Evidence from USA and India. Royal Society Open Science, 4, 160605.
9. Capraro, V. (2017a). Does the truth come naturally? Time pressure increases honesty in one-shot deception games. Economics Letters, 158, 54-57.
10. Capraro, V. (2017b). Who lies? A meta-analysis of the effect of sex, age, and education on honesty. Available at SSRN: https://ssrn.com/abstract=2930944.
11. Charness, G., & Rabin, M. (2002). Understanding social preferences with simple tests. The Quarterly Journal of Economics, 117, 817-869.
12. Childs, J. (2012). Gender differences in lying. Economics Letters, 114, 147-149.
13. Corgnet, B., Espín, A. M., Hernán-González, R. (2015). The cognitive basis of social behavior: Cognitive reflection overrides antisocial but not always prosocial motives. Frontiers in Behavioral Neuroscience, 9, 287.
14. Debey, E., Verschueren, B., Crombez, G. (2012). Lying and executive control: An experimental investigation using ego depletion and goal neglect.
15. Dreber, A., & Johannesson, M. (2008). Gender differences in deception. Economics Letters, 99, 197-199.
16. Erat, S., & Gneezy, U. (2012). White lies. Management Science, 58, 723-733.
17. Ezquerra, L., Rodriguez-Lara, I., & Kolev, G. (2017). Gender differences in cheating: Loss vs. gain framing. Economics Letters, 163, 46-49.
18. Fehr, E., & Schmidt, K. (1999). A theory of fairness, competition, and cooperation. The Quarterly Journal of Economics, 114, 817-868.
19. Fischbacher, U. Föllmi-Heusi, F. (2013). Lies in disguise – An experimental study on cheating. Journal of the European Economic Association, 11, 525-547.
20. Friesen, L., & Gangadharan, L. (2012). Individual level evidence of dishonesty and the gender effect. Economics Letters, 117, 624-626.
21. Hurkens, S., & Kartik, N. (2009). Would I lie to you? On social preferences and lying
aversion. *Experimental Economics*, 12, 180-192.

22. Kartik, N. (2009). Strategic communication with lying costs. *Review of Economic Studies*, 76, 1359-1395.

23. Konrad, K., Lohse, T. & Simon, S. (forthcoming). Deception under time pressure: Conscious decision or a problem of awareness? *Journal of Behavioral and Experimental Economics*. Preprint available at https://www.econstor.eu/handle/10419/168171.

24. Lotz, S. (2015). Spontaneous giving under structural inequality: Intuition promotes cooperation in asymmetric social dilemmas. *PLoS ONE*, 10, e131562.

25. Gino, F., Schweitzer, M. E., Mead, N. L., & Ariely, D. (2011). Unable to resist temptation: How self-control depletion promotes unethical behavior. *Organizational Behavior and Human Decision Processes*, 115, 191-203.

26. Goodman, J. K., Cryder, C. E., Cheema, A. (forthcoming). Deception under time pressure: Conscious decision or a problem of awareness? *Journal of Behavioral Decision Making*, 26, 213-224.

27. Gneezy, U. (2005). Deception: The role of consequences. *American Economic Review*, 95, 384-394.

28. Gneezy, U., Rockenbach, B., & Serra-Garcia, M. (2013). Measuring lie aversion. *Journal of Economic Behavior and Organization*, 93, 293-300.

29. Gneezy, U., Kajackaite, A., & Sobel, J. (forthcoming). Lying aversion and the size of the pie. *American Economic Review*.

30. Gravelle, J. G. (2009). Tax Havens: International tax avoidance and evasion. *National Tax Journal*, 68, 727-753.

31. Gunia, B. C., Wang, L., Huang, L., Wang, J., & Murnighan, J. K. (2012). Contemplation and conversation: Subtle influences of moral decision making. *Academy of Management Journal*, 55, 13-33.

32. Horton, J. J., Rand, D. G., & Zeckhauser, R. J. (2011). The online laboratory: Conducting experiments in a real labor market. *Experimental Economics*, 14, 399-425.

33. Kajackaite, A., & Gneezy, U. (2017). Incentives and cheating. *Games and Economic Behavior*, 102, 433-444.

34. Levine, E. E., & Schweitzer, M. (2014). Are liars ethical? On the tension between benevolence and honesty. *Journal of Experimental Social Psychology*, 53, 107-117.

35. Levine, E. E., & Schweitzer, M. (2015). Prosocial lies: When deception breeds trust. *Organizational Behavior and Human Decision Processes*, 26, 88-106.

36. Mason, W., & Suri, S. (2012). Conducting behavioral research on Amazon’s Mechanical Turk. *Behavioral Research Methods*, 44, 1-23.

37. Mazar, N., Amir, O., Ariely, D. (2008). The dishonesty of honest people: A theory of self-concept maintenance. *Journal of Marketing Research*, 45, 633-644.

38. Mead, N. L., Baumeister, R. F., Gino, F., & Ariely, D. (2009). Too tired to tell the truth: Self-control resource depletion and dishonesty. *Journal of Experimental Social Psychology*, 45, 594-597.

39. Open Science Collaboration (2015) Estimating the reproducibility of psychological science. *Science*, 349, 943-953.

40. Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon Mechanical Turk. *Judgment and Decision Making*, 5, 411-419.

41. Paolacci, G., Chandler, J. (2014). Inside the Turk: Understanding Mechanical Turk as a participation pool. *Current Directions in Psychological Science*, 23, 184-188.
42. Rand, D. G. (2016). Cooperation, fast and slow: Meta-analytic evidence for a theory of social heuristics and self-interested deliberation. *Psychological Science, 27*, 1192-1206.
43. Rand, D. G., Brescoll, V. L., Everett, J. A. C., Capraro, V., Barcelo, H. (2016). Social heuristics and social roles: Intuition favors altruism for women but not for men. *Journal of Experimental Psychology: General, 145*, 389-396.
44. Rand, D. G. Greene, J. D., Nowak, M. A. (2012). Spontaneous giving and calculated greed. *Nature*, 489, 427-430.
45. Rand, D. G., Peysakhovich, A., Kraft-Todd, G. T., Newman, G. E., Wurzbacher, O., Nowak, M. A., Greene, J. D. (2014). Social heuristics shape intuitive cooperation. *Nature Communications, 5*, 3677.
46. Shalvi, S., & de Dreu, C. K. W. (2014). Oxytocin promotes group-serving dishonesty. *Proceedings of the National Academy of Sciences, 111*, 5503-5507.
47. Shalvi, S., Eldar, O., & Bereby-Meyer, Y. (2012). Honesty requires time (and lack of justifications). *Psychological Science, 23*, 1264-1270.
48. Sheremeta, R. M., Shields, T. W. (2013). Do liars believe? Beliefs and other-regarding preferences in sender-receiver games. *Journal of Economic Behavior and Organization, 94*, 268-277.
49. Spence, S. A., Farrow, T. F. D., Herford, A. E., Wilkinson, I. D., Zheng, Y., Woodruff, P. W. R. (2001). Behavioural and functional anatomical correlates of deception in humans. *Neuroreport, 12*, 2849–2853.
50. Van’t Veer, A. E., Stel, M., & van Beest, I. (2014). Limited capacity to lie: Cognitive load interferes with being dishonest. *Judgment and Decision Making, 9*, 199-206.
51. Walczyk, J. J., Roper, K. S., Seemann, E., Humphrey, A. M. (2003). Cognitive mechanisms underlying lying to questions: response time as a cue to deception. *Applied Cognitive Psychology, 17*, 755–774.
52. Weisel, O., Shalvi, S. (2015). The collaborative roots of corruption. *Proceedings of the National Academy of Sciences, 112*, 10651-10656.
53. Wiltermuth, S. S. (2011). Cheating more when the spoils are split. *Organizational Behavior and Human Decision Processes, 115*, 157-168.
Experimental instructions

Screen 1

Welcome to this HIT.

This is an anonymous HIT. It will take about ten minutes. For your participation, you will earn 50c and some additional money to be determined later.

Screen 2

In the next screens, you will generate two pieces of information:

- A POSITION, which will be a number, for example 14.
- A LIST of potential bonuses between 1 and 90, such as: 23 73 34 22 2 11 54 21 44 3 22 6 89 45 67 23 65 46 77 1 86 5 4

Your bonus for this HIT will be the one in the position you generated. Thus, in this case, it will be 45c, because 45 is in position 14.

What is your job?

REPORT the POSITION you generated.

IMPORTANT: This survey is anonymous. We do not know the position that you will generate.

We now ask some comprehension questions in order to ascertain that you understood the situation.

Assume that you generate:

POSITION: 13
LIST: 35 24 36 82 14 3 29 21 55 64 35 33 67 2 13 21 65 46 8 43 32

What position did you generate?
(blank text box where to type the answer here)

What would be your bonus if you report the position you generated?
(blank text box where to type the answer here)

What position could you report if you wanted to earn a bigger bonus?
(blank text box where to type the answer here)
Assume that you receive:

POSITION: 9
LIST: 53 8 24 27 76 61 65 14 34 25 22 33 73 68 86 2 13 25 71 78 63 27 51 11

What **position** did you generate?
(blank text box where to type the answer here)

What would be your **bonus** if you report the position you generated?
(blank text box where to type the answer here)

What **position** could you report if you wanted to earn a bigger bonus?
(blank text box where to type the answer here)

Congratulations, you have passed all comprehension questions.

In the next screen, you will generate a POSITION. In the screen after, you will generate a SEQUENCE of potential bonuses and you will be asked to report the POSITION you generated.

Remember that you will receive a payment in cents equal to the number in the position you report.

**Screen 5 (Unlucky condition)**

POSITION: 19

Please take note of this position on a piece of paper.

Now click the next button in order to generate a sequence.

**Screen 5 (Lucky condition)**

POSITION: 22

Please take note of this position on a piece of paper.

Now click the next button in order to generate a sequence.

**Screen 6 (Time Pressure condition)**
What POSITION did you generate?
(Blank text box where to type the answer here)

*Screen 6 (No Time Constraint condition)*

What POSITION did you generate?
(Blank text box where to type the answer here)