Chapter 2.3

What does a young cheater look like? An innovative approach

Pietro Battiston[1], **Simona Gamba**[2], **Valentina Rotondi**[3]
[1]University of Milan-Bicocca, Milan, Italy, [2]University of Verona, Verona, Italy, [3]Bocconi University, Milan, Italy

Chapter Outline

JEL Classification: C90, D91

1. Introduction

Personality traits matter. We could summarize with these simple words a vast literature in social sciences dedicated to explaining the behavior of individuals, acting alone or within societies. Examples abound in several economic contexts spanning from the intention to become a social entrepreneur (Nga and Shamuganathan, 2010), to management of household finances (Brown and Taylor, 2014), to labor market outcomes (Fletcher, 2013). Similarly vast is the literature on cheating, justified by the profound economic and social consequences of such behavior.

In this chapter, we link these two growing strands of literature by studying the relation between experimental measures of cheating behavior among adolescents and personality measures obtained through a questionnaire.

The first consistent finding from the experimental literature on cheating is that some (not all) individuals are dishonest, i.e., when facing the opportunity to lie in order to extract a gain (with the lie typically concerning the result of a dice roll, or a fair coin toss), a sizable share of individual do so: that is, the proportion of individuals reporting a win usually exceeds the objective probability of a win, while still being smaller (often considerably smaller) than one (Abeler et al., 2018). This general result overshadows, however, a huge heterogeneity in

Dishonesty in Behavioral Economics. https://doi.org/10.1016/B978-0-12-815857-9.00006-6

the observed individual cheating behavior. Most individuals are willing to cheat only a little (Shalvi et al., 2011), some entirely refrain from lying, while others lie to the maximum possible extent (Fischbacher and Föllmi-Heusi, 2013). This observed heterogeneity, coupled with the fact that individuals who cheat in the lab tend to cheat also in the field (Cohn and Maréchal, 2016), raises the question of which characteristics of an individual's personality influence her decision to lie.

As a precondition for any discussion, we all know that people care about their self-image and struggle to preserve it (Mazar et al., 2008). This struggle imposes a cost, of psychological nature, to the cheater, which changes according to the context. As a matter of example, we know that the decision to lie implies a different psychological cost when people have to report their immoral intentions before acting (Jiang, 2013), when acting dishonestly hurts (or benefit) others (e.g., Fischbacher and Föllmi-Heusi, 2013), when temporally distancing the decision task from the payment of the reward (Ruffle and Tobol, 2014), when individuals are under scrutiny (Ostermaier and Uhl, 2017; Pierce et al., 2015), when they act alone or in groups (Kocher et al., 2018), and when they have a potential accomplice (Barr and Michailidou, 2017).

Only recently some papers have considered the importance of personality traits in cheating behavior. In a recent contribution, Pfattheicher et al. (2018) use economically incentivized cheating paradigms (a dice-rolling paradigm and a coin-toss paradigm) to show that, in line with previous literature (Hilbig and Zettler, 2015; Kleinlogel et al., 2018), the basic personality trait of Honesty-Humility from the HEXACO personality model (Ashton and Lee, 2007) is negatively related to cheating behavior. That is, they identify a relation between cheating and personality which goes beyond the dark personality traits of narcissism, Machiavellianism, psychopathy, and sadism already studied by Jones and Paulhus (2017)—no effect is found instead when a third-party scrutiny is simulated by presenting the subjects with stylized watching eyes. Interestingly, personality traits have different effects on different types of lies. Jonason et al. (2014) show that while Machiavellianism is related to white lies, narcissism is related to lying for self-gain, whereas psychopathy is related to telling lies for no reason. In a companion paper, Baughman et al. (2014) show that psychopathy predicts scholastic cheating. In another recently published paper, Heck et al. (2018) address the question of power and sample size by exploiting the richness of 16 studies ($N = 5002$), assessing dishonest behavior in an incentivized, one-shot, cheating paradigm. While confirming the negative correlation between cheating and Honesty-Humility, which was independent of other personality, situational, or demographic variables, they found that one other trait only from the "Big Five" (Agreeableness) was (negatively) associated with unethical decision-making, although the strength of the relation is much lower than with the Honesty-Humility trait.

Although cheating, lying, and deception are diffused behaviors both in the adult and in the young population, there is relatively limited evidence of the determinants of cheating among children and adolescents in the economic literature. Some relevant exceptions are Bucciol and Piovesan (2011), Glätzle-Rützler and Lergetporer (2015), Maggian and Villeval (2016), Korbel (2017), Battiston et al. (2018), Cadsby et al. (2019); see Heyman et al. (2019) for a recent review of this stream of research.

In this chapter we use data gathered from an experiment conducted with scout groups from Trentino-Alto Adige, a region in Northern Italy, during their summer camps in August 2017. The experiment, employing a revised version of the fair coin toss paradigm proposed by Bucciol and Piovesan (2011), was followed by a rich questionnaire including, beyond standard demographic questions, a detailed self-assessment of risk aversion, "Big Five" personality traits, level of trust in other people and propensity to break the rules. In our empirical analysis, we employ a principal component analysis (PCA, henceforth), a dimensionality reduction technique aimed at capturing common moments in the data, to gauge the extent to which different personality traits might influence the propensity to cheat. We then reanalyze the decision to cheat by using decision tree classifiers, a very popular technique in the machine learning literature, which also achieve the aim of dimensionality reduction, but focusing on the interaction between variables rather than on (linear) common moments across them.

Our results suggest that, while risk propensity is not a strong overall predictor of cheating behavior, self-confidence is irrespectively of the beneficiary of the payment being the individual or the patrol. The use of decision tree classifiers confirms these results, supports the validity of the PCA approach, and further suggests that, *among less self-confident subjects*, risk propensity does explain a larger propensity to cheat.

The remainder of this chapter is organized as follows: Section 2 presents the data gathered from the experiment, Section 3 presents the empirical analysis, while Section 4 concludes.

2. Experimental framework

We base our analysis on an experiment run in August 2017, during the summer camps of six scout troops from Trentino-Alto Adige, a region in Northeastern Italy. All groups were member of AGESCI, a Catholic association that includes the vast majority of scouts in Italy. The general mission of scouting is to contribute to the education of young people, through a value system, and methods, that are shared by all scouts around the world. All members of the Scout Movement are required to adhere to the Scout Promise and Scout Law. The Scout Law emphasizes the importance of honesty and loyalty: the decision to cheat in our experiment can be particularly salient. During the year, members of a same scout troop carry out together multiple activities, culminating in the summer camp; hence, the troop itself is akin to a society, with its rules, values, roles, and objectives. Each troop in turn is subdivided in multiple patrols, members of whom collaborate even more closely.

Our experiment involved a gender-balanced population of 160 young scouts, aged 12–16, all from the same region. They were regrouped in 31 patrols, in turn forming 6 troops, each taking part in one experimental session. We study the results from a detailed end of experiment questionnaire and from the experiment itself, a modified version of the coin task proposed by Bucciol and Piovesan (2011). The basic experimental task consists in each subject randomly drawing, from an envelope, a piece of paper where either the amount "€0" or "€10" is printed, entering a tent, and writing on a separate ticket the amount read. Such ticket would determine the payoff for the participant. In our experiment, each individual would in fact make *two* of such decisions, independently and simultaneously, by picking and transcribing two different pieces of papers, identified by different colors. The only difference was that in one case (yellow) total secrecy was guaranteed as to their extracted value, while in the other case (blue) any cheating behavior would have been observed ex post by *patrol members*, in a subsequent phase in which subjects would reenter the tent by patrols. The entire procedure was explained to participants in advance, including the fact that actual payoffs, distributed in the form of vouchers at the end of the session, would depend from one only of the two experimental tasks (total secrecy or ex-post patrol scrutiny), to be randomly determined, after the experiment, via a coin toss. While one participant was carrying out the activity, other troop members were involved in traditional scout games and songs. After the experimental session was over,[a] participants were asked to scatter through the camp area and individually fill a paper-and-pencil questionnaire.[b]

Our statistical analysis is based on comparing the share of respondents reporting “€10” against a binomial distribution. Indeed, the experiment was designed in order to ensure that experimenters could not detect individual cheating (pieces of paper reporting the numbers drawn were put in a bin to be burned after the experiment): we cannot know whether an individual who reported “€10” has cheated or was lucky. Hence, given our interest in the propensity to cheat at the individual level, we attenuate the inherent noise in the outcome variables by analyzing the *mean* of the two responses (the one under total secrecy and the one subject to ex post patrol scrutiny), with its value normalized to 0 (having reported “€0” in both cases), 0.5 (having reported “€0” in one of the two cases), or 1 (having reported “€10” in both cases).[c] This increases the power of our analysis, as the probability for a noncheater to report the best possible outcome (“€10” twice) is 0.25, rather than 0.5—or in other terms, the likelihood of a subject reporting “€10” being noncheater is 0.25, rather than 0.5.

a. The session involved another experiment, taking place after the one studied in this chapter. Participants knew beforehand they would participate in two experiments, but the second was described only once the first was over.

b. See Battiston et al. (2018) for a more detailed description of experimental procedures.

c. The reported outcome under secrecy is missing for five subjects: for them, the “mean” only includes the reported outcome under ex post patrol scrutiny.

Importantly, in three randomly drawn sessions/troops, subjects had earnings paid with individual vouchers, as is standard in the experimental literature on cheating, while in the other three sessions/troops, payments were cumulated at the patrol level and paid with collective vouchers (in a between-individual treatment). In both cases, vouchers were to be spent at the local scouting store, selling both goods for private, individual use (e.g., backpacks, uniforms, sleeping bags) or goods for public, collective use (e.g., tents, pots, and other team equipments). Battiston et al. (2018) have already shown that this treatment has no discernible effect: in what follows, we pool the results from all six sessions unless specified otherwise.

Answers from the questionnaire (see the Appendix) cover socio-demographic information (gender, age, whether any of the parents was born outside Italy, household size) as well as several individual characteristics that could affect the propensity to cheat, regrouped in four main categories:

1. Trust in other people, with questions adapted from the 2008 European Value Survey, including
   - a general Yes/No question about trust in other people, and
   - five more detailed questions specifying the recipients of trust (e.g., people in general vs member of one's troop/patrol) and admitting responses ranging from 0 to 10, where larger values denote higher levels of trust.[d] The choice to include detailed questions specifying the recipients of trust derives from the fact that the literature on trust and misbehavior generally finds a differential effect of *general* trust, i.e., trust toward unknown members of the society, vs *particular* trust. While confidence in unknown others is widely recognized as an essential component of positive social capital, since it leads to widespread cooperation (Putnam, 2001) with a resulting positive effect in terms of social and economic development (e.g., Adhikari and Goldey, 2010), confidence *only* in known people is usually conducive to negative social capital (Banfield, 1958) and it can constitute a burden in terms of economic development. As a matter of example, particular trust has been shown to be conducive to corruption (Uslaner, 2004), while high levels of interpersonal trust have been found to reduce corruption (Bjørnskov, 2006);
2. Propensity to break the rules to improve the condition of other individuals, depending on their identity (e.g., family member, patrol members, or people met for the first time), measured from 1 (*low propensity*) to 4 (*high propensity*)[e];

d. In what follows we consider as "trust_takeadv" the *complement to 10* of the answer to the question "how much do you agree that most people would try to take advantage of you if they had the chance?", for which larger values denoted *lower* trust.

e. Notice that, for ease of exposition, we analyze the *complement to 5* of answers to the questions reported in the Appendix. Hence, larger values correspond to a larger propensity to break the rules.

3. Personality traits, investigated through a revised Italian version of the Ten-Item Personality Inventory (Chiorri et al., 2015). For each of the "Big Five" traits (extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience), two questions were proposed: one directly asking about the trait, and one asking about the counterpoised trait. Possible answers to each question range from 1 (*completely disagree*) to 7 (*completely agree*);
4. Risk propensity, measured with a reduced version of the Domain-Specific Risk-Taking (DOSPERT) Scale (Blais and Weber, 2006), including questions about risk attitudes in the recreational, financial, ethical, health, and social domains. We extracted out of the original questions two from each domain. The scale goes from 1 to 7, where 1 represents a low risk propensity and 7 a high risk propensity. Although we are aware of the fact that risk aversion can be more effectively measured through laboratory experiments, we preferred not to further complicate the experimental design and to introduce a possibility of hedging. We refer the reader to the existing literature on the correlation between experimental and questionnaire measures of risk aversion (e.g., Attanasi et al., 2018).

In total, we consider 38 variables extracted from the questionnaire: their list and descriptive statistics are provided in Table 1.

The winning rate is $\pi = 0.541$: a one-sided t-test shows this is significantly higher ($p = 0.067$) than the objective probability of extracting €10 ($\pi = 0.5$). 25 individuals present at least one missing value for the variables of interest and are hence dropped from the subsequent analysis. We verify that the propensity to cheat for dropped individuals is not significantly different than for other individuals.

3. Analysis

Our data set includes a large number of variables, which are purposely strongly correlated among them. This is true for instance for the 10 questions concerning risk aversion, and for the pairs of questions concerning the "Big Five" personality traits.

Rather than basing our analysis on an arbitrary selection of variables and on ad-hoc independence assumptions, we run a PCA. We use this technique with the aim to reduce the dimensionality of the data while capturing common moments, defined by linear combinations of individual variables. Importantly, our variables can be seen as regrouped in clusters (risk, trust, …) but at the same time are of quite different nature from one cluster to another. That is, it is reasonable to expect that different components will correspond, at least approximately, to such clusters—while it is unlikely that a single component explains most of the variability. Identifying a reduced number of important components will then allow us to analyze how they shape the individual propensity to cheat.

TABLE 1 Descriptive Statistics for Explanatory Variables Involved in the Analysis

	Count	Mean	Std	Min	Median	Max
male	158	0.513	0.501	0	1	1
age	158	14.316	1.216	12	14	16
foreign	160	0.069	0.254	0	0	1
hhsize	159	4.824	1.675	2	5	20
trust	158	0.620	0.487	0	1	1
trust_general	160	5.956	1.760	1	6	10
trust_troop	160	7.900	1.668	1	8	10
trust_patrol	160	8.681	1.623	2	9	10
trust_helpful	160	6.356	1.944	0	6	10
trust_takeadv	160	4.956	2.318	0	5	10
rule_family	159	3.660	0.645	1	4	4
rule_neighbors	160	2.181	0.816	1	2	4
rule_known	159	3.333	0.709	1	3	4
rule_unknown	157	1.911	0.779	1	2	4
rule_oneself	158	3.228	0.874	1	3	4

(Continued)

TABLE 1 Descriptive Statistics for Explanatory Variables Involved in the Analysis—cont'd

	Count	Mean	Std	Min	Median	Max
rule_oth_religion	159	2.943	0.859	1	3	4
rule_oth_nation	159	3.075	0.776	1	3	4
rule_patrol	160	3.300	0.734	1	3	4
personality_extroverted	158	4.259	1.817	1	5	7
personality_difficult	156	3.269	1.739	1	3	7
personality_trustworthy	158	5.329	1.239	1	6	7
personality_worried	158	3.778	1.917	1	4	7
personality_open	159	5.503	1.466	1	6	7
personality_reserved	159	3.277	1.876	1	3	7
personality_understanding	158	5.177	1.426	1	5	7
personality_disorganized	158	3.722	1.777	1	4	7
personality_calm	157	4.599	1.454	1	5	7
personality_traditionalist	159	3.799	1.757	1	4	7
risk_recreational_I	159	3.541	1.824	1	4	7
risk_financial_I	156	3.455	1.546	1	4	7
risk_financial_II	159	1.950	1.504	1	1	7
risk_ethical_I	158	2.525	1.599	1	2	7

risk_health_I	158	2.734	1.940	1	2	7
risk_social_I	157	4.261	1.614	1	4	7
risk_recreational_II	158	4.418	2.212	1	5	7
risk_health_II	159	4.057	1.887	1	4	7
risk_social_II	158	4.481	1.847	1	5	7
risk_ethical_II	158	3.095	2.006	1	3	7

Of the 38 components returned by the PCA decomposition (same as the number of input variables, by design), 13 correspond to eigenvalues larger than 1—meaning that each of them explains more variability than the average individual variable—and 5 components correspond to eigenvalues larger than 2 (see Fig. 1). Given our goal of tracing back the cheating behavior to a limited number of easily interpretable individual traits, we focus on the latter five components—which together explain 38.24% of variance in the data.

We can interpret the main components by looking at their *loading factors* (presented in Table 2), that is, at the role of each input variable in their composition. The results of this analysis reflect the structure of the questionnaire, but at the same time provide interesting insights about the interrelation between variables. In particular, some clear features can be identified among the most important components.

- The section of the questionnaire concerning risk attitudes is quantitatively important (10 questions) and considers a relatively narrow aspect of personality—propensity to risk. Hence, it is not surprising that the first component is mostly related to *risk propensity*: risk variables all bear loading factors which are positive, and in some cases large. Nevertheless, the magnitude of the loading factors varies significantly, from 0.096 (risk_financial_II)[f] to 0.301 (risk_health_II).[g] Concerning personality, in Fig. 2, we can notice that

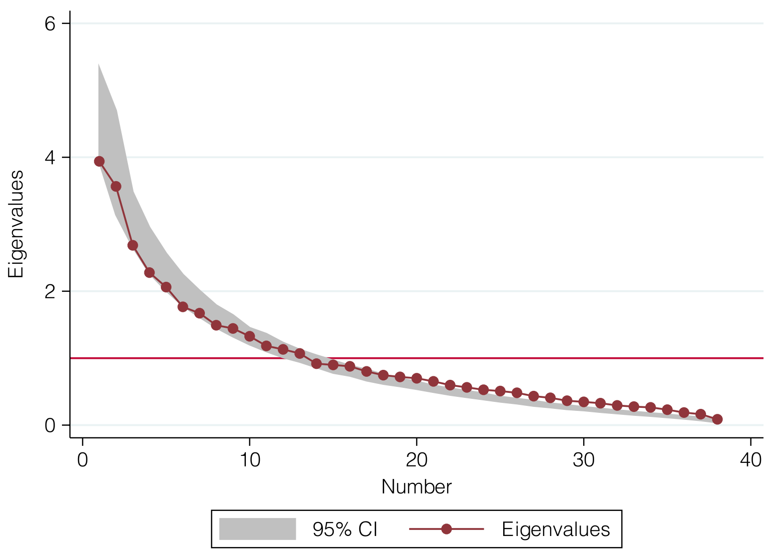

FIG. 1 Scree plot of PCA components. *Note*: Each *dot* corresponds to a PCA component, ranked according to the corresponding eigenvalue. A larger eigenvalue denotes a higher explanatory power for the associated component. The *horizontal line* denotes the value of 1—the threshold value above which a component explains more than the average original variable. 13 components have an eigenvalue larger than 1, and 5 larger than 2.

f. Propensity to “Betting a day’s income on the outcome of a sporting event”.
g. Propensity to “Walking home alone at night in an unsafe area of town”.

TABLE 2 Loading Factors for Main PCA Components

	Comp1	Comp2	Comp3	Comp4	Comp5
male	0.058	−0.131	0.059	−0.328	−0.114
foreign	0.06	−0.018	−0.072	0.044	−0.18
age	0.227	−0.053	0.163	−0.029	−0.017
hhsize	−0.023	0.081	−0.043	0.161	−0.077
trust	−0.12	0.182	0.207	0.082	0.02
trust_general	−0.086	0.238	0.269	0.091	−0.055
trust_troop	−0.145	0.281	0.264	0.023	0.017
trust_patrol	−0.091	0.28	0.243	−0.005	−0.031
trust_helpful	−0.107	0.224	0.249	0.013	−0.008
trust_takeadv	−0.191	0.16	0.116	−0.031	0.01
rule_family	0.119	0.205	−0.278	−0.286	−0.055
rule_neighbors	−0.104	0.135	−0.172	0.145	−0.043
rule_known	0.147	0.341	−0.23	−0.1	−0.004
rule_unknown	0.068	0.074	−0.09	0.313	0.018
rule_oneself	0.192	0.154	−0.242	−0.18	−0.019
rule_oth_religion	0.117	0.319	−0.23	0.147	0.086

(Continued)

TABLE 2 Loading Factors for Main PCA Components—cont'd

	Comp1	Comp2	Comp3	Comp4	Comp5
rule_oth_nation	0.059	0.343	−0.231	0.141	−0.043
rule_patrol	0.155	0.287	−0.197	−0.003	−0.162
personality_extroverted	0.183	0.079	0.263	−0.014	−0,022
personality_difficult	0.219	−0.112	−0.052	0.208	0.175
personality_trustworthy	−0.103	0.068	−0.067	−0.032	0.54
personality_worried	−0.101	−0.068	−0.074	0.396	0.02
personality_open	0.143	0.112	0.183	−0.054	0.288
personality_reserved	−0.091	−0.136	−0.214	0.305	0.068
personality_understanding	−0.191	0.128	−0.017	0.057	0.289
personality_disorganized	0.209	−0.054	0.137	0.199	−0.209
personality_calm	−0.025	0.017	−0.036	−0.237	0.24
personality_traditionalist	−0.105	−0.15	−0.122	−0.097	0.286
risk_recreational_I	0.24	0.011	0.037	−0.082	0.194
risk_financial_I	0.181	0.022	0.044	0.018	0.079
risk_financial_II	0.096	0.002	0.053	0.064	−0.105

risk_ethical_I	0.11	−0.027	0.021	0.276	0.046
risk_health_I	0.261	−0.013	0.095	0.089	−0.008
risk_social_I	0.178	−0.021	0.091	0.215	0.305
risk_recreational_II	0.267	0.06	0.105	−0.099	0.248
risk_health_II	0.301	0.026	0.143	−0.002	−0.096
risk_social_II	0.265	0.039	0.116	0.073	0.059
risk_ethical_II	0.215	−0.186	−0.08	0.014	0.015

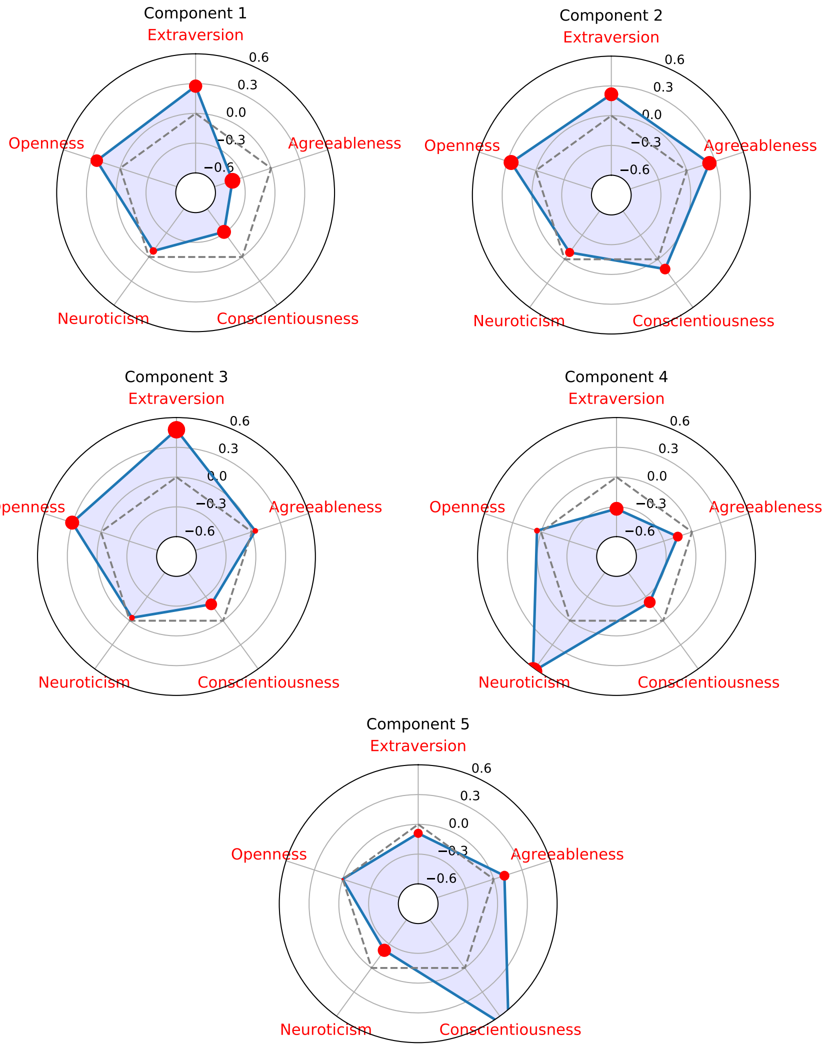

FIG. 2 Summary of personality traits related to the first five PCA components. *Note*: Each "trait score" is calculated as the loading factor for one question of the "personality" section minus the loading factor for the opposed question (see Section 2 for details). *Dashed pentagons* indicate value 0 (expected location of *bullets* if, e.g., answers to personality questions were random); the size of *bullets* indicates absolute value of the trait score (i.e., their importance).

this first component is positively related to extraversion and openness, and negatively to conscientiousness and agreeableness, in accordance with the existing literature on the relationship between the Big Five and risk attitude (Nicholson et al., 2005) and with what the intuition would suggest for less risk averse individuals. No clear relation is found with the last of the Big

Five traits, that is, neuroticism (obtaining a score close to 0). Notice, indeed, that such score is the combination of two questionnaire items[h] which, while being conceived as counterpoised in the Ten-Item Personality Inventory (Chiorri et al., 2015), can be expected to have a similar, negative, relation to risk. In fact, this is, among the 10 personality questions, the only pair of questions which do *not* have opposite loading coefficients for the first component (−0.101 and −0.025, respectively). In addition, the attitude toward risk correlates positively with the propensity to break the rules, and negatively to the measures of trust. Consistently with the existing literature, it also correlates positively with being a male (although the absolute value of the loading factor is small) (Miller, 2011) and with age (Duell et al., 2018).

- If the first component was clearly related to the questionnaire section concerning risk, the second component prominently features variables from the section concerning trust and from the section concerning the propensity to break the rules: all loading factors for the related variables are positive, and most of them are larger than 0.2 (see Table 2).
- At a first sight, the fact that this second component relates positively both to measures of trust *and* to propensity to break the rules might seem odd—given that the two sections mostly had opposite signs in the first component. But this is instead a natural consequence of the fact that components of PCA analysis are *uncorrelated* (if they were not, their informational content would overlap, and their explanatory power would not be maximized). Hence, the second component is capturing the main feature of data which is *not explained* by the first component: namely, that, controlling for risk attitudes, subjects with higher levels of trust are more inclined to break the rules. Interestingly, the second plot in Fig. 2 shows that this component mostly correlates with *positive* traits: in fact, all pairs of personality-related variables have opposite signs, and the largest loading factor (in absolute value) is the −0.150 for "traditionalist, routine-bound." Thus, this component seems to capture a dimension of freedom and *self-confidence* which is orthogonal to risk aversion.
- While the third, fourth, and fifth components have significantly lower explanatory power, they are worth surveying as they are each strongly related to—almost dominated by—a different personality trait from the Big Five (see Fig. 2). Component 3 is related to extraversion, openness, and trust, denoting an *outwards* oriented personality. Component 4 is related to high levels of neuroticism, low extraversion and in general a *reserved* and anxious attitude, which seems to be more common among female subjects (see the coefficient of −0.328 for "male"). Component 5 is instead strongly related to conscientiousness, and in particular it presents a very large loading factor (0.540) for trustworthiness, signaling a *reliable* person. It is worth mentioning that only two of the five pairs of personality questions have

h. Being "Worried, anxious" (question 4) and being "calm, emotionally stable" (question 9).

matching signs, and that, among components considered so far, this is the one presenting the largest absolute value for the loading factor of "foreign" (−0.180): notice, however, from Table 1, that this variable is strongly unbalanced, taking value 1 for less than 7% of the sample.

Fig. 3 represents the loading factors for each variable for the first two components. It allows for an easy spatial characterization of the different realms covered by our questionnaire. Indeed, we can observe that, with the exception of the personality questions (which are meant to be strongly differentiated), each family of questions occupies a specific area of the plane. Variables from sections "trust" and "rule" are well identified in terms of each of the two main components; instead, "risk" variables, which form the backbone of component 1, *risk propensity*, are not strongly related to component 2, *self-confidence*: recall that the two components are orthogonal by design.

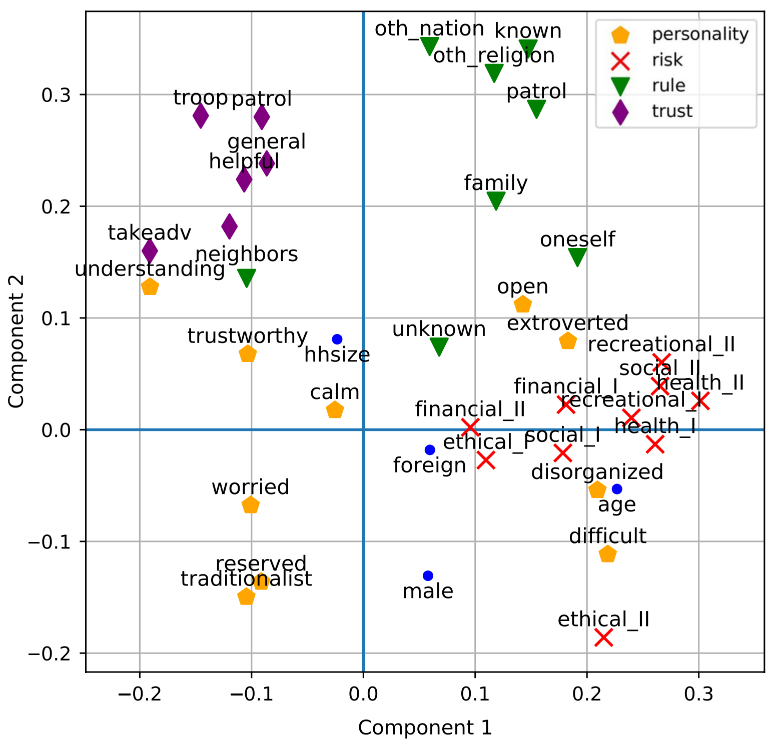

FIG. 3 Factor loadings for the first two components. *Note*: *Graphic representation* of the first two columns from Table 2, characterizing the two main components. Each *marker* denotes 1 of the 38 original variables employed in the analysis, with the *shape* denoting the section of the questionnaire (according to the legend), and the *label* identifying the specific item. For instance, the *triangle* with label "oneself" denotes the loading factors for the "rule_oneself" variable. The *rhombus* without label refers to the simple ``trust" variable; simple dots correspond to the general demographic variables.

3.1 Linear analysis

Having identified the main components of the questionnaire data, we are left with a reduced number of variables which can explain a large share of the data variability, and which can be used to explain the propensity to cheat, by regressing the reported outcomes from the cheating experiment on the components themselves. Results are presented in Table 3, Column (1). Importantly, since components are uncorrelated by design, results are robust to the inclusion of further components. Similarly, results are qualitatively unchanged if only the

TABLE 3 **Results From PCA-Based Linear Specifications**

	(1) Full	(2) Full	(3) Individual	(4) Patrol
pca1—risk propensity	0.010	0.009	0.003	0.016
	(0.011)	(0.012)	(0.020)	(0.013)
pca2—self-confidence	0.038**	0.037**	0.048	0.033
	(0.016)	(0.016)	(0.028)	(0.020)
pca3—outwards	0.000	0.002	−0.012	0.026
	(0.018)	(0.017)	(0.027)	(0.026)
pca4—reserved	0.003	0.006	−0.000	0.009
	(0.020)	(0.021)	(0.033)	(0.027)
pca5—reliable	0.003	0.003	0.010	−0.011
	(0.022)	(0.023)	(0.028)	(0.035)
PatrolPayment		−0.026		
		(0.071)		
_cons	0.530***	0.543***	0.537***	0.509***
	(0.034)	(0.033)	(0.033)	(0.062)
R^2	0.046	0.048	0.056	0.060
N	135	135	66	69

Note: Clustered standard errors (at the patrol level) in *parentheses*. Columns (3) and (4) disaggregate the analysis based on the recipients of payments. *$p<0.10$, **$p<0.05$, ***$p<0.01$.

first two components—which are characterized by eigenvalues larger than 3—are included in the analysis.

Contrary to what one might expect, the first component, *risk propensity*, is not significant ($p=0.383$). This might seem even more surprising because, as already observed, seven out of eight questions concerning the propensity to break the rules have a positive loading factor for such component. However, we can observe that our experiment—as well as most experiments on cheating in the literature—did not involve any *uncertainty* regarding the probability of being observed by the experimenter or being punished. This can explain the apparent inconsistency of our results with those reported by Bucciol et al. (2013, 2019), who find, respectively, that bus passengers traveling without a valid ticket and students frequently cheating in written exams (contexts which involve a risk of being caught and sanctioned) are more risk tolerant. On the other hand, the propensity to break the rules takes a more central role in the second component, *self-confidence* (see Table 2), which is instead strongly significant ($p=0.027$). That is, once removing uncertainty from the decision-making context, a self-confident attitude is a crucial explanation of the propensity to cheat.

It is important to remember that participants were subject to a between-individual treatment that potentially shaped their decision to cheat: in three troops, payments were at the individual level, while in the remaining three troops, they were aggregated in a voucher assigned to each patrol (see Section 2). As already mentioned, this treatment did not affect the propensity to cheat. This is visible in Column (2) of Table 3: the coefficient for the "PatrolPayment" variable is not significant ($p=0.717$), while other coefficients are virtually unchanged—in particular, the second PCA component, *self-confidence*, is still strongly significant. We further control for a possible interaction between the treatment and the individual characteristics, i.e., for personality traits having different effects depending on the beneficiary of the lie, by running the analysis separately on sessions with individual payments (Columns (3)) and sessions with patrol payment (Column (4)). Although the significance of the second component disappears ($p=0.112$ and 0.116, respectively) due to the smaller sample sizes, we can see that both the sign and the magnitude of the coefficient are consistent with our previous results.

For completeness, Table 4 summarizes the results for several model specifications, in which the outcome is regressed on the constant and a single variable at a time. In line with results presented in Table 3, we find no relation between the propensity to cheat and our treatment variation (PatrolPayment). None of the personality variables is significant after adopting a Bonferroni correction,[i] confirming the important role of the PCA in identifying traits that explain the pro-

i. Multiple hypothesis testing can increase the probability of incorrect rejection of true null hypotheses (type I error). The Bonferroni correction neutralizes this risk by testing each hypothesis, for a given desired significance level α, at a level of $\frac{\alpha}{m}$, where m is the total number of hypotheses to be tested.

TABLE 4 Results for Different Model Specifications

	Coeff	SE
male	−0.089	(0.067)
foreign	−0.032	(0.120)
age	−0.041	(0.024)
hhsize	0.020	(0.013)
trust	−0.015	(0.061)
trust_general	0.023	(0.017)
trust_troop	0.020	(0.021)
trust_patrol	0.029	(0.023)
trust_helpful	0.002	(0.016)
personality_extroverted	−0.008	(0.014)
personality_difficult	−0.006	(0.019)
personality_trustworthy	0.007	(0.026)
personality_worried	−0.012	(0.017)
personality_open	0.023	(0.021)
personality_reserved	−0.029**	(0.013)
personality_understanding	0.012	(0.022)
personality_disorganized	−0.004	(0.013)
personality_calm	0.000	(0.019)
personality_traditionalist	−0.020	(0.021)
risk_recreational_I	0.009	(0.015)
risk_financial_I	0.011	(0.019)
risk_financial_II	0.049**	(0.019)
risk_ethical_I	−0.001	(0.018)
risk_health_I	0.007	(0.019)
risk_social_I	−0.002	(0.016)
risk_recreational_II	0.010	(0.014)
risk_health_II	0.018	(0.013)
risk_social_II	0.017	(0.017)

(Continued)

TABLE 4 Results for Different Model Specifications—cont'd

	Coeff	SE
risk_ethical_II	0.006	(0.014)
trust_takeadv	0.020*	(0.010)
rule_family	0.040	(0.038)
rule_neighbors	0.030	(0.031)
rule_known	0.053	(0.035)
rule_unknown	0.041	(0.027)
rule_oneself	0.047	(0.031)
rule_oth_religion	0.061*	(0.035)
rule_oth_nation	0.048	(0.046)
rule_patrol	0.020	(0.027)
PatrolPayment	−0.031	(0.069)

Note: Clustered standard errors (at the patrol level) in *parentheses* (no variable is significant after applying Bonferroni correction). $*p<0.10$, $**p<0.05$, $***p<0.01$. Each regression is run on 135 observations.

pensity to cheat. More specifically, the PCA improves our analysis both because it allows the identification of traits which are the composition of different variables, and because thanks to the dimension reduction it alleviates the problem of multiple hypotheses testing. It might still worth noticing that variables for which the relation is significant (without Bonferroni correction) all have loading coefficients larger than 0.1 in PCA component 2, related to self-confidence, with the exception of "risk_financial_II," which is the risk variable presenting the lowest loading factor in the PCA component 1, related to risk aversion.

3.2 Nonlinear analysis

The analysis run so far focuses on the importance of single traits in explaining cheating behavior and accounts, through the PCA transformation, for the strong collinearity characterizing the original data. However, it does not explore the possible interaction effects between different variables. Indeed, given that PCA components are orthogonal among them, there is no obvious candidate interaction term which could be introduced in the analysis. At the same time, even limiting to the five main components, the possible interaction terms amount to 10, which would make a linear analysis difficult to interpret and prone to spurious results. In what follows, we therefore apply more flexible methods that allow us to predict cheating behavior in a theory-agnostic way, and to compare the results with what we found so far.

Decision tree classifiers are a very general technique which is extremely popular in the machine learning literature and practice, in particular, when the number of available features is large compared to the number of observations. Given a Boolean outcome variable—defining two *classes* within the sample—and a potentially large number of explanatory variables, a decision tree is built by splitting the sample according to the variable and threshold value that best separate the two classes, and by iterating the analysis on each of the two subsamples separately. In other terms, the sample is ultimately partitioned in a number of subsamples such that the *impurity* of each (typically identified with the Gini index of the outcome variable within the subsample) is minimized.

In a general sense, the decision tree technique also achieves dimensionality reduction, since it selects the variables that best explain the outcome. However, to the extent that PCA components capture actual traits of experiment participants more succinctly than original variables, the same should hold for their interaction effects; hence, ceteris paribus, a decision tree based on the PCA components, should outperform a decision tree based on the original variables.

Decision trees potentially allow for a very large number of degrees of freedom but, given the limited number of observations in our sample, in what follows we focus on trees including only two levels—i.e., three branching points. We safeguard against the risk of *over-fitting* by testing the out-of-sample prediction power of our models. To this aim, we implement a *cross-validation* procedure: we randomly split multiple times the population in two disjunct samples, using one sample to train the model (i.e., build the regression tree), and the other to validate it (i.e., predict the outcome variable). The prediction power of a model is then computed as the average fit over the different iterations.

Concerning the outcome variable, given our focus on *classification* of subjects, we refrain from recurring to the mean of the two individual decisions, as done in Section 3.1, since that results in a variable which can assume three values (0, 0.5, 1)—and considering them as mere categories would disregard the important fact that they are ordered. Hence, we include both reported outcomes of each individual separately. The potential pitfall related to this approach is that, to the extent that the two reported outcomes of each individual are correlated, using (a sample including) one of the two to predict the other introduces again a risk of over-fitting. We solve this problem by ensuring that, in the cross-validation procedure, the two samples never have individuals in common—that is, the random subsample selection is made at the individual, rather than at the observation, level.

A leave-one-out procedure (in which each individual in the sample is in turn removed from the training set and the rest of the sample is used to predict its outcome) returns a pseudo-R^2 of 0.544 when using the 38 original variables, and of 0.581 when using the five main PCA components.[j] Fig. 4 plots the results of

j. Consistently with the linear analysis above, in what follows we limit our analysis to the first 5 components.

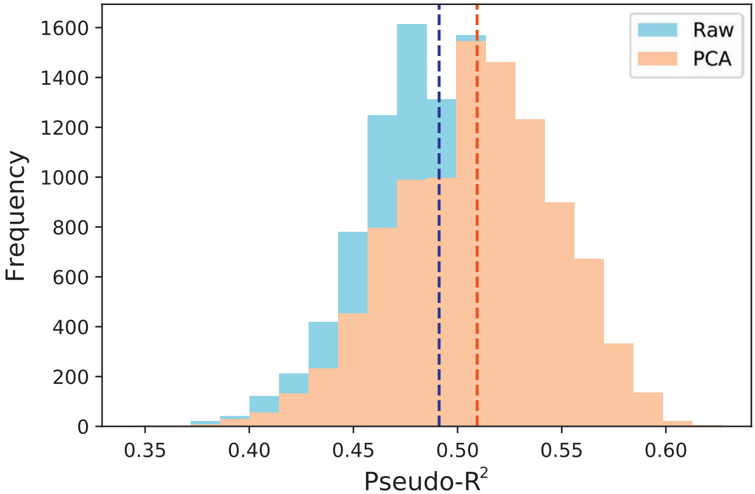

FIG. 4 Distribution of pseudo-R^2 from depth 2 classification trees. *Note*: Results from 10,000 iterations of twofolds cross-validation. In order to guarantee balancedness of the samples, each pair (training sample, testing sample) was subsequently reversed and reused. Notice that the distribution is concentrated in a limited number of values, as the pseudo-R^2 is the result of the normalization of an integer number (the number of observations which were correctly classified).

10,000 iterations of twofolds cross-validation: the prediction based on the five main PCA components performs systematically better than the prediction based on the original variables ($p = 0.000$ from a Mann–Whitney U test).

Fig. 5 features the structures obtained when training the tree on the entire sample. The color of each node is related to the predicted value of the outcome variable, with blue and red denoting, respectively, more and less cheating. Each node is characterized by a Gini index, a sample size, and two values, indicating, respectively, the in-sample frequency of reporting "€0" and "€10," weighted so that the two classes have equal mass in the overall sample (root node). Finally, each branching (nonleaf) node reports, at the top, the variable and the threshold which determine the sample split between the two children nodes—i.e., the split which minimizes the Gini index of each subsample.

In the decision tree for PCA components (Fig. 5A), component 2, *self-confidence*, is placed in the root branch, consistently with its preeminence in the linear analysis presented above: as can be read in the two children nodes, we confirm results from Section 3.1 that more self-confident individuals (comp2 > 0.4865) tend to cheat more. This is a robust result, as it also happens in 65.6% of cases in the twofolds cross-validation exercise. The branching nodes at the second level also constitute the most common structure observed in the twofolds cross-validation. On the left, in the subsample of individuals with a relatively low self-confidence, we observe that those with lower *risk propensity* (comp1 ≤ 2.4033) tend to report "€10" less often than the risk lovers. On the right, in the subsample of more self-confident individuals, component 4,

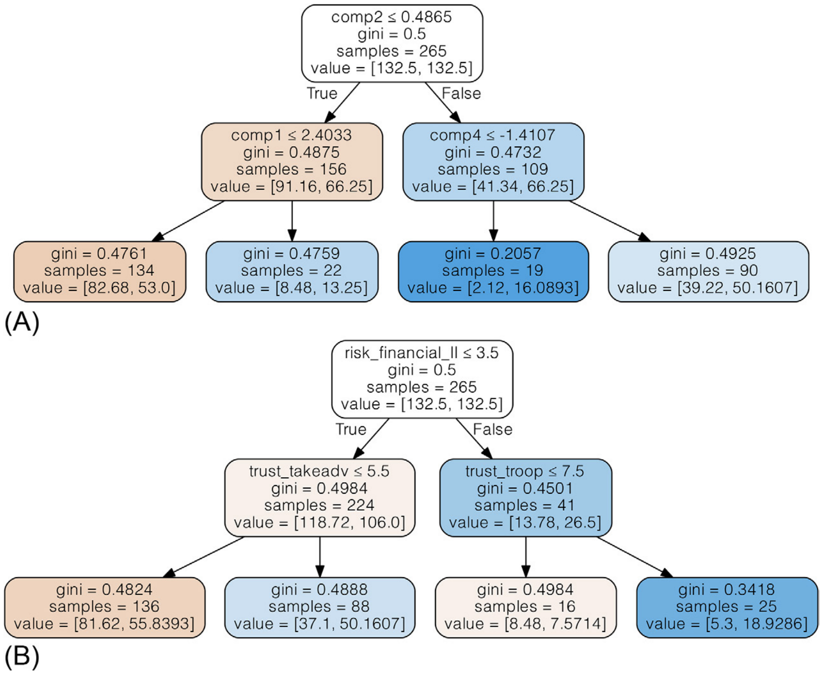

FIG. 5 Depth 2 decision tree structure. *Note*: Decision trees trained on the entire sample, employing the five main PCA components (A) or original variables (B). Each branching node is identified by the condition that separates the two children nodes. In addition, each node reports the Gini index, size, and outcome frequencies for the subsample it represents. Frequencies are weighted in such a way as to have both outcomes (0 and 10) equally represented (in the root node), as unbalanced samples otherwise result in biased decision trees. This explains why the elements of "value" are not integer numbers.

reserved, determines the subsequent sample splitting. The fact that this is the most important component to be strongly related to gender (being more prominent for females) suggests that women (comp4 > 1.4107) tend to cheat less.

The decision trees for the original variables are not only less powerful predictors, but they are also much less stable. The structure featured in Fig. 5B is among the most frequently observed in the twofold cross-validation exercise, but there is a large variability—the variable "risk_financial_II" is the root tree in only 8.37% of cases. Nevertheless, it is instructive to observe once more that such variable is precisely the one, among questions related to risk, that had the *lowest* loading factor in the PCA component 1.

4. Conclusion

In this chapter we focus on the role played by personality traits in terms of cheating behavior.

We exploit data from a detailed questionnaire and a cheating experiment to study the determinants of cheating in adolescents aged 12–16. Through a PCA analysis, we identify the traits of participants that best summarize the data variability: we clearly identify a first component related to risk propensity and a second component related to self-confidence. We show that, differently from what one might expect, risk propensity is not a strong overall predictor of cheating behavior. Instead, self-confident subjects tend to cheat significantly more. Interestingly, the beneficiary of the payment (the individual or the patrol)—i.e., our between-individual treatment—does not affect the propensity to cheat, neither the role of different individual traits in explaining this propensity.

Through the use of decision tree classifiers we confirm results found in linear analysis that self-confidence (PCA component 2) is the driving predictor of the propensity to cheat. Looking at the subsequent level in the tree, we also see that, *among less self-confident subjects*, a specific measure of propensity toward risk does explain a larger propensity to cheat. We show that, in general, the PCA approach makes decision tree classifiers significantly more accurate and stable than when individual variables are used.

Appendix. Questionnaire

Below is the translation from Italian of the questionnaire that participants answered at the end of the experimental session. Each question is accompanied by the label of the corresponding variable, in square brackets. Asterisks denote questions for which answers were rescaled or combined in the analysis—see main text for details.

- Assigned totem:
- Year of birth *[age]*
- Place of birth:
- Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?
  ☐ Yes ☐ No (you can't be too careful) *[trust]*
  [Each of the following six questions was followed by check boxes with numbers from 0 to 10]
- From 0 to 10, how much do you tend to trust people in general? *[trust_general]*
- From 0 to 10, how much do you tend to trust members of your troop? *[trust_troop]*
- From 0 to 10, how much do you tend to trust members of your patrol?*[trust_patrol]*
- From 0 to 10, how much do you agree that most people would try to take advantage of you if they had the chance? *[trust_takeadv*]*
- From 0 to 10, how much do you agree that most of the time people try to be helpful? *[trust_helpful]*
- From 0 to 10, taking all things together, how happy would you say you are?
- Was your father born in Italy? ☐ Yes ☐ No *[foreign*]*

- Was your mother born in Italy? ☐ Yes ☐ No *[foreign*]*
- How many people are in your family, including you? *[hhsize]*
- For each of the following groups of people, how willing would you be to break the rules in order to improve their condition?

  [Each of the following items was followed by check boxes with numbers from 1–4, where 1 was labeled as "very willing" and 4 as "definitely not willing"]

  - Your family *[rule_family*]*
  - Your neighbors *[rule_neighbors*]*
  - Someone you know well *[rule_known*]*
  - Someone you meet for the first time *[rule_unknown*]*
  - Yourself *[rule_oneself*]*
  - Someone of a different religion than yours *[rule_oth_religion*]*
  - Someone of a different nationality than yours *[rule_oth_nation*]*
  - Your patrol *[rule_patrol*]*
- Please read the following personality traits and rate how well each pair of adjectives describes you. Even if you think that one characteristic describes you better than the other, using the following scale:

  [A 7-item Likert scale was used. Each of the following items was followed by check boxes with numbers from 1 to 7.]
  1. extroverted, exuberant *[personality_extroverted]*
  2. difficult, adversarial *[personality_difficult]*
  3. trustworthy, self-disciplined *[personality_trustworthy]*
  4. worried, anxious *[personality_worried]*
  5. open to new experiences, with many interests *[personality_open]*
  6. reserved, silent *[personality_reserved]*
  7. understanding, affectionate *[personality_understanding]*
  8. disorganized, absent-minded *[personality_disorganized]*
  9. calm, emotionally stable *[personality_calm]*
  10. traditionalist, routine-bound *[personality_traditionalist]*

- For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation. Provide a rating from Extremely Unlikely to Extremely Likely, using the following scale:
  [A 7-item Likert scale was used. Each of the following items was followed by check boxes with numbers from 1 to 7. Labels in square brackets are provided for reference and did not appear in the printed questionnaire.]
  1. Going down a ski run that is beyond your ability. *[risk_recreational_I]*
  2. Investing 10% of your annual income in a start-up. *[risk_financial_I]*
  3. Betting a day's income on the outcome of a sporting event. *[risk_financial_II]*
  4. Revealing a friend's secret to someone else. *[risk_ethical_I]*
  5. Riding a motorcycle without a helmet. *[risk_health_I]*

6. Speaking your mind about an unpopular issue in a patrol meeting. *[risk_social_I]*
7. Bungee jumping off a tall bridge. *[risk_recreational_II]*
8. Walking home alone at night in an unsafe area of town. *[risk_health_II]*
9. Moving to a city far away from your parents. *[risk_social_II]*
10. Not returning a wallet you found that contains €200. *[risk_ethical_II]*

References

Abeler, J., Nosenzo, D., Raymond, C., 2018. Preferences for truth-telling. Econometrica . Forthcoming.

Adhikari, K.P., Goldey, P., 2010. Social capital and its downside: the impact on sustainability of induced community-based organizations in Nepal. World Dev. 38 (2), 184–194. Elsevier.

Ashton, M.C., Lee, K., 2007. Empirical, theoretical, and practical advantages of the Hexaco model of personality structure. Pers. Soc. Psychol. Rev. 11 (2), 150–166. Sage Publications Sage CA: Los Angeles, CA.

Attanasi, G., Georgantzís, N., Rotondi, V., Vigani, D., 2018. Lottery-and survey-based risk attitudes linked through a multichoice elicitation task. Theor. Decis. 84 (3), 341–372. Springer.

Banfield, E.C., 1958. The Moral Basis of a Backward Society. 3 Glencol, New York, p. 4.

Barr, A., Michailidou, G., 2017. Complicity without connection or communication. J. Econ. Behav. Organ. 142, 1–10. Elsevier.

Battiston, P., Gamba, S., Rizzolli, M., Rotondi, V., 2018. Lies have long legs. Cheating, Public Scrutiny and Loyalty in Teams." (Working Paper).

Baughman, H.M., Jonason, P.K., Lyons, M., Vernon, P.A., 2014. Liar liar pants on fire: cheater strategies linked to the dark triad. Personal. Individ. Differ. 71, 35–38. Elsevier.

Bjørnskov, C., 2006. The multiple facets of social capital. Eur. J. Polit. Econ. 22 (1), 22–40. Elsevier.

Blais, A.-R., Weber, E.U., 2006. A domain-specific risk-taking (DOSPERT) scale for adult populations. Judgm. Decis. Mak. 1 (1), 33–47.

Brown, S., Taylor, K., 2014. Household finances and the 'big five' personality traits. J. Econ. Psychol. 45, 197–212. Elsevier.

Bucciol, A., Piovesan, M., 2011. Luck or cheating? A field experiment on honesty with children. J. Econ. Psychol. 32 (1), 73–78. Elsevier.

Bucciol, A., Landini, F., Piovesan, M., 2013. Unethical behavior in the field: demographic characteristics and beliefs of the cheater. J. Econ. Behav. Organ. 93, 248–257.

Bucciol, A., Cicognani, S., Montinari, N., 2019. Cheating in academia: the relevance of social factors. In: Bucciol, A., Montinari, N. (Eds.), Dishonesty in Behavioral Economics.

Cadsby, B., Song, F., Yang, X., 2019. Dishonesty among children: a lab-In field experiment on the impact of rural/urban status and parental migration. In: Bucciol, A., Montinari, N. (Eds.), Dishonesty in Behavioral Economics. Elsevier.

Chiorri, C., Bracco, F., Piccinno, T., Modafferi, C., Battini, V., 2015. Psychometric properties of a revised version of the Ten Item Personality inventory. Eur. J. Psychol. Assess. 31, 109–119. Hogrefe Publishing.

Cohn, A., Maréchal, M.A., 2016. Laboratory measure of cheating predicts school misconduct. Econ. J. 128 (615), 2743–2754. Wiley Online Library.

Duell, N., Steinberg, L., Icenogle, G., Chein, J., Chaudhary, N., Di Giunta, L., Dodge, K.A., 2018. Age patterns in risk taking across the world. J. Youth Adolesc. 47 (5), 1052–1072. Springer.

Fischbacher, U., Föllmi-Heusi, F., 2013. Lies in disguise—an experimental study on cheating. J. Eur. Econ. Assoc. 11 (3), 525–547. Oxford University Press.

Fletcher, J.M., 2013. The effects of personality traits on adult labor market outcomes: evidence from siblings. J. Econ. Behav. Organ. 89, 122–135. Elsevier.

Glätzle-Rützler, D., Lergetporer, P., 2015. Lying and age: an experimental study. J. Econ. Psychol. 46, 12–25. Elsevier.

Heck, D.W., Thielmann, I., Moshagen, M., Hilbig, B.E., 2018. Who lies? A large-scale reanalysis linking basic personality traits to unethical decision making. Judgm. Decis. Mak. 13 (4), 356–371. Society for Judgment; Decision Making.

Heyman, G., Lee, K., Compton, B., Zhao, L., 2019. Dishonesty in young children. In: Bucciol, A., Montinari, N. (Eds.), Dishonesty in Behavioral Economics. Elsevier.

Hilbig, B.E., Zettler, I., 2015. When the Cat's away, some mice will play: a basic trait account of dishonest behavior. J. Res. Pers. 57, 72–88. Elsevier.

Jiang, T., 2013. Cheating in mind games: the subtlety of rules matters. J. Econ. Behav. Organ. 93, 328–336. Elsevier.

Jonason, P.K., Lyons, M., Baughman, H.M., Vernon, P.A., 2014. What a tangled web we weave: the dark triad traits and deception. Personal. Individ. Differ. 70, 117–119. Elsevier.

Jones, D.N., Paulhus, D.L., 2017. Duplicity among the dark triad: three faces of deceit. J. Pers. Soc. Psychol. 113 (2), 329. American Psychological Association.

Kleinlogel, E.P., Dietz, J., Antonakis, J., 2018. Lucky, competent, or just a cheat? Interactive effects of honesty-humility and moral cues on cheating behavior. Pers. Soc. Psychol. Bull. 44 (2), 158–172. SAGE Publications Sage CA: Los Angeles, CA.

Kocher, M.G., Schudy, S., Spantig, L., 2018. I lie? We lie! Why? Experimental evidence on a dishonesty shift in groups. Manag. Sci. 64 (9), 3995–4008. https://doi.org/10.1287/mnsc.2017.2800.

Korbel, V., 2017. Do we lie in groups? An experimental evidence. Appl. Econ. Lett. 24 (15), 1107–1111. Taylor & Francis.

Maggian, V., Villeval, M.C., 2016. Social preferences and lying aversion in children. Exp. Econ. 19 (3), 663–685. Springer.

Mazar, N., Amir, O., Ariely, D., 2008. The dishonesty of honest people: a theory of self-concept maintenance. J. Market. Res. 45 (6), 633–644. American Marketing Association.

Miller, G., 2011. The Mating Mind: How Sexual Choice Shaped the Evolution of Human Nature. Anchor Books, New York.

Nga, J.K.H., Shamuganathan, G., 2010. The influence of personality traits and demographic factors on social entrepreneurship start up intentions. J. Bus. Ethics 95 (2), 259–282. Springer.

Nicholson, N., Soane, E., Fenton-O'Creevy, M., Willman, P., 2005. Personality and domain-specific risk taking. J. Risk Res. 8 (2), 157–176. Routledge.

Ostermaier, A., Uhl, M., 2017. Spot on for liars! How public scrutiny influences ethical behavior. PloS One 12 (7), 1–11. Public Library of Science.

Pfattheicher, S., Schindler, S., Nockur, L., 2018. On the impact of honesty-humility and a cue of being watched on cheating behavior. J. Econ. Psychol. Forthcoming, Elsevier.

Pierce, L., Snow, D.C., McAfee, A., 2015. Cleaning house: the impact of information technology monitoring on employee theft and productivity. Manag. Sci. 61 (10), 2299–2319. INFORMS.

Putnam, R.D., 2001. Bowling Alone: The Collapse and Revival of American Community. Simon; Schuster.

Ruffle, B.J., Tobol, Y., 2014. Honest on mondays: honesty and the temporal separation between decisions and payoffs. Eur. Econ. Rev. 65, 126–135. Elsevier.

Shalvi, S., Handgraaf, M.J.J., De Dreu, C.K.W., 2011. Ethical manoeuvring: why people avoid both major and minor lies. Br. J. Manag. 22, S16–S27. Wiley Online Library.

Uslaner, E.M., 2004. Trust and corruption. In: Lambsdorff, J.G., Taube, M., Schramm, M. (Eds.), The New Institutional Economics of Corruption. Routledge, pp. 90–106.