Finance Research Letters 58 (2023) 104373

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

How does probabilistic harm affect dishonesty? An experiment

Štěpán Bahník, Marek Vranka *

Faculty of Business Administration, Prague University of Economics and Business, náměstí Winstona Churchilla 4, Prague, 130 67, Czech Republic

ARTICLE INFO

JEL:
C93
D91

Keywords:
Dishonesty
Bribery
Experiment
Justification

ABSTRACT

Dishonest actions, while beneficial to perpetrators, can have significant negative effects on financial markets and organizations. The caused harm is, however, often unclear and unpredictable, possibly making dishonesty easier to justify. We conducted an experiment where participants could break a rule for increased rewards, potentially harming a third party. By manipulating the probability of harm while maintaining the size of expected harm constant, we explore how the probability of harm influences dishonesty. Contrary to expectations, our results suggest that the manipulation does not impact the dishonest behavior. These findings underscore the complexity of dishonest behavior in contexts relevant to finance.

1. Introduction

High-profile financial scandals, such as the $2 billion cash discrepancy in Wirecard's books, inevitably seize the public's attention. Yet, these infamous episodes are but a small fraction of the many more instances of dishonest behavior that likely exist hidden within the everyday operations (Soltes, 2019). While prior work has mainly focused on corporate governance mechanisms to explain the occurrence of financial misconduct (Cumming et al., 2018), it is important to realize that individuals' characteristics and situational factors play pivotal roles in both initiating and perpetuating dishonest behaviors. Despite the extensive body of research dedicated to the study of dishonesty in recent years (Gerlach et al., 2019; Reurink, 2019), there remains a gap in our understanding of how the uncertainty about its negative consequences influences individuals' willingness to engage in it. This study aims to address this gap by investigating the impact of varying probabilities of harm on the propensity to behave dishonestly.

In the vein of the rational crime framework proposed by Becker (1968), numerous studies have explored the effects of monitoring (Broadstock and Chen, 2021; Xiong et al., 2021) and punishment probability (Friesen, 2012; Laske et al., 2018; Nagin, 2013; Teodorescu et al., 2021) on financial misconduct, crime, and dishonest behavior. However, when people decide whether to act in such a way, they take into account not only external costs associated with the probability and size of potential punishment, but also the internal psychological costs of rule-breaking (Thielmann and Hilbig, 2019).

Of note, the psychological costs are heavily influenced by the impacts that dishonest behavior has on others. For example, people intuitively refrain from directly harming specific individuals, but are much more likely to behave dishonestly when nobody (or only an institution's budget) is harmed (Köbis et al., 2019; Leib et al., al.,2021). It follows that when dishonest behavior has only uncertain negative consequences, people may find it easier to justify their rule-breaking (Hauser et al., 2007). Dishonest behavior may not lead to direct certain harm to society or specific third parties for a variety of reasons (Abbink and Serra, 2012). For example, a corrupt SEC official may take a bribe intended to influence a decision that does not depend only on one person, such as when the decision has to be approved by multiple people. In such a situation, the person taking the bribe could believe that her behavior does not have any certain

* Corresponding author.
E-mail addresses: bahniks@seznam.cz (Š. Bahník), vranka.marek@gmail.com (M. Vranka).

https://doi.org/10.1016/j.frl.2023.104373
Received 30 May 2023; Received in revised form 19 August 2023; Accepted 27 August 2023
Available online 28 August 2023
1544-6123/

negative consequences. Similarly, a fund manager might take on riskier assets for the promise of a significant personal kickback, rationalizing that the portfolio could potentially yield high returns, making the exact harm to the fund's investors uncertain.

Despite the potential importance of harm's uncertainty in justifying dishonesty, the effects of differing probability of harm are still poorly understood. Some experiments (Abbink et al., 2002; Cameron et al., 2009) even fail to find any effect of harm caused by dishonest behavior. However, Barr and Serra (2009) note that this absence of the effect might be caused by specifics of used experimental designs in which dishonesty either harms all participants (Abbink et al., 2002) or those harmed are able to reciprocate (Cameron et al., 2009). Correspondingly, more recent studies find that information about negative externalities effectively deters dishonest behavior in the form of bribery (Guerra and Zhuravleva, 2019; Senci et al., 2019).

However, studies attempting to explore how the probability of negative consequences affects dishonest behavior are sparse and inconclusive. Rahimi (2020) finds that halving the probability of causing harm increases the likelihood of taking bribes, but the effect is not significant at the conventional 5% level. Moreover, Rahimi (2020) keeps the size of harm constant across conditions, effectively lowering the expected size of harm with lowering its probability. The study design is therefore unable to distinguish whether any difference in bribe-taking is caused by the uncertainty of harm or rather by the lower expected harm.

While the effect of lower expected harm could be explained in line with the previous findings about lower negative externalities leading to more dishonest behavior, making the harmful effects uncertain might affect dishonesty in a unique way by creating "a moral wiggle room" for participants. It has been suggested that people sometimes avoid information and prefer to stay ignorant about negative consequences of their behavior to retain a positive self-image (Dana et al., 2007). In a similar fashion, when a harm caused by dishonest behavior is uncertain, participants may preserve their self-image by believing that the harm will not occur in the specific instance when they decide to behave dishonestly.

On the other hand, the effect of size of a harm on its subjective perception is not linear; people are not sufficiently sensitive to the scope of the harm. This insensitivity to scope has been demonstrated in a number of domains, such as valuation of human lives (Dickert et al., 2015) and of environmental harm (Desvousges et al., 2010). Therefore, we expect that the lower probability of harm increases the likelihood of dishonest behavior even when the size of the harm correspondingly increases to keep the expected size constant.

In the present study, we contribute to the study of the effect of uncertainty of negative consequences on dishonest behavior. We use a sorting task in which participants can break a rule for personal gain, potentially causing harm to a third party. By varying the probability of harm while keeping the expected size of harm constant, we provide a nuanced understanding of how uncertainty of negative outcomes influences dishonest behavior.

Our results suggest that the probability of negative consequences does not significantly affect dishonest behavior when the expected size of the consequences is held constant. This finding extends our understanding of factors influencing financial misconduct, and implies that uncertainty of negative consequences of such behavior does not uniquely contribute to its prevalence.

2. Experimental design

Preregistration of the study as well as data, analysis scripts, and materials can be found at https://osf.io/5zqm4/wiki/home/ and https://osf.io/pqzyr/.

2.1. Participants

Participants were recruited from the laboratory subject pool consisting predominantly of university students (~74%) and women (~71%). For the sake of higher anonymity, we did not ask the participants any demographic questions. Three hundred participants finished the study. Following pre-registered exclusion criteria, we excluded 8 participants who did not complete the task properly[1] and performed the analysis with the remaining 292 participants. The participants took on average 13 min to complete the task, earning on average 121 CZK (~5.7 USD) for themselves.

2.2. Procedure and design

We modified a sorting task previously used for the laboratory study of bribe-taking (Bahník and Vranka, 2022a, 2022b; 2018) for online administration. Participants are asked to sort 200 objects appearing one-by-one on their computer screen according to the objects' color (see https://osf.io/c69rm/wiki/home/ for full instructions and screenshots of the task). They are awarded 3 points for each sorted object, even when it is sorted incorrectly. Randomly selected ~15% of the objects are shown with a number corresponding to "a bribe"[2] that participants can take to earn an additional reward (varying from 30 to 180 points in 30-point increments)[3] if they disregard the rule and sort the object according to its shape. However, for each incorrectly sorted object, there is a chance that a charity[4] loses a certain number of points from the 2000 points endowed to it at the beginning. The loss simulates negative societal effects of not performing given work according to the given rule. The loss of points for the charity—if it occurred—is highlighted by

[1] That is, participants who sort at least 10 times an object in the task according to neither its color, nor its shape.

[2] While we use the term "bribe" for simplicity and in line with Vranka and Bahník (2018; Bahník & Vranka, 2022a, 2022b), the additional reward can also represent embezzled money or any gain from dishonest behavior in general.

[3] Participants are not told the probability with which a bribe occurs, nor the distribution of its sizes.

[4] The charity was chosen by each participant from two well-known Czech charitable organizations before the task.

increasing the size of the text displaying the current reward for the charity and changing its color to red for one second.

The experiment has been conducted online using a custom-written Python (Django) and Javascript web application. Participants are explained the task, complete 10 practice trials and then proceed with the task itself. The practice trials do not involve any reward or bribes and serve only to accustom participants with the sorting task. Afterwards, participants are explained the possibility to earn money for themselves by sorting the objects and the consequences of breaking the sorting rule and sorting objects with numbers according to their shape instead of color. In the control group, participants are informed that the charity loses 200 points whenever a participant sorts the object incorrectly. In the medium-probability group, there is a 50% probability the charity loses 400 points when the object is sorted incorrectly. In the low-probability group, the loss is 2000 points and the probability 10%. At the end of the session, all points are converted to a monetary reward using the rate 10 points = 1 CZK (~0.04 USD) and paid to the participants and charities.

3. Results

Incorrect sorting in trials without a bribe is rare, with only 0.9% of trials not sorted according to color, showing that participants are generally able to sort the objects correctly.

Trial-level analysis is conducted using a mixed-effect linear regression.[5] The correctness of object classification serves as the dependent variable. The model includes only trials where the object is correctly sorted according to either shape or color and a bribe is offered. Order of the trial, squared order of the trial (rescaled to range from-0.5 to 0.5), and linear and quadratic contrasts for bribe size are included as covariates to account for some of the variance in the dependent variable (Bahník and Vranka, 2022a, b, and 2018, show that both bribe size and trial order predict bribe-taking in the task). The groups are compared using linear and quadratic contrasts to model various possible relationships between the probability of harm and dishonest behavior (Schad et al., 2020). Random intercepts for participants are included in the model. Random slopes for participants are included for order and bribe size. Correlations are included only between the random effects for the same variable (i.e., order of the trial and squared order of the trial; linear and quadratic contrasts for bribe size).

Fig. 1 shows the probabilities of taking bribes of different sizes in each experimental condition. Table 1 shows the results of the model. Participants are more likely to take higher bribes, but the quadratic effect of bribe size is not significant. Participants are less likely to take bribes in later trials and the quadratic effect suggests a concave relationship between trial order and the probability of taking a bribe. Most importantly, there is no significant linear or quadratic effect of condition.

4. Conclusion

Unlike in many economic experiments, in real life people are seldom certain what would be the full consequences of their actions. When harmful consequences do not necessarily follow a dishonest action, people may use this uncertainty as a moral wiggle room and thus be more likely to behave dishonestly. In the present study we have explored how making the harmful consequences less certain affects dishonest behavior.

Contrary to our initial expectations, our results show that the probability of the harm caused to a charity does not significantly affect the rate of dishonest behavior; that is, the likelihood of dishonesty when it always causes harm does not differ from the likelihood when the probability of causing harm is 50% or only 10%. The estimate of the size of the effect of our manipulation of the probability of harm suggests that other factors, such as bribe size and learning throughout the task, are much more important in predicting whether participants behave dishonestly, or not.

As the expected harm is held constant across the conditions, it is possible that the effect of the lower probability of the negative consequences is fully compensated by the larger size of the loss. The results complement similar recent findings by Celse et al. (2019) that show the absence of the effect of uncertainty of obtaining benefits from cheating on the likelihood of behaving dishonestly.

The processes that can lead people to behave more dishonestly when the negative consequences of dishonesty are uncertain might be also counteracted by opposing processes. For example, when deciding from description rather than experience, people overestimate small probabilities, so the lowest probability of negative consequences might seem subjectively higher than it is objectively (Erev and Roth, 2014; Tversky and Kahneman, 1992), at least when first deciding whether to act dishonestly. Potentially large consequences for dishonesty in the low-probability group might elicit fear and could therefore loom larger than would correspond to their nominal value (cf. Slovic, 1987).

These mechanisms might work against the expected processes that would lead people to behave more dishonestly when the negative consequences of dishonesty were less likely. Given that we do not examine participants' decision process during the task or their perception of the task, these possible processes cannot be distinguished. A process-tracing study may clarify whether the manipulation has no effect or whether it influences different people differently (Schulte-Mecklenbeck et al., 2017). Future studies should also attempt to disentangle the probability and size of harm caused by dishonest behavior by manipulating both factors separately.

The study suggests that the probability of harm by itself does not affect dishonest behavior: the potential for no harm does not appear to provide a moral cushion for individuals to rationalize dishonest conduct. Consequently, it could be advantageous to underscore even the relatively remote and uncertain harm caused by fraudulent activities, such as insider trading or financial

[5] See Gomila (2021) for arguments for the use of linear regression for binary variables. A mixed-effect logistic regression yields similar results: https://osf.io/t7cph/

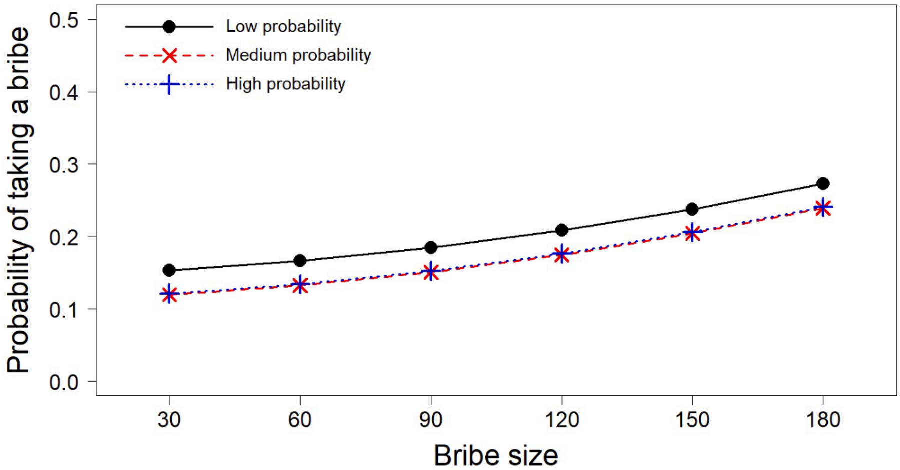

Fig. 1. The relationship between bribe size and the probability of taking a bribe. The graph shows predicted probabilities from a model without order effects.

Table 1
The results of the study. The numbers in parentheses represent 95% confidence intervals around the regression coefficients. Given that all predictors range from -0.5 to 0.5, their coefficients can be interpreted as the probability difference in bribe-taking between highest and lowest values of the predictors. Random effects are not shown for simplicity.

	Bribe-taking
Condition (linear)	-0.022
	(-0.074, 0.029)
Condition (quadratic)	0.015
	(-0.039, 0.069)
Bribe size (linear)	0.103***
	(0.078, 0.128)
Bribe size (quadratic)	0.016
	(-0.0004, 0.033)
Trial number (linear)	-0.071***
	(-0.106, -0.037)
Trial number (quadratic)	-0.034**
	(-0.060, -0.009)
Constant	0.176***
	(0.145, 0.207)
Observations	8642

*Note:**$p<0.05$; **$p<0.01$; ***$p<0.001$.

misreporting, as a part of comprehensive deterrence strategies. However, it is important to consider the full spectrum of factors motivating dishonest behavior. Indeed, a multifaceted approach addressing aspects such as the perceived probability of detection, the severity of penalties, and the establishment of robust ethical norms and corporate governance structures might prove more effective in deterring dishonest conduct (Houdek, 2019). By focusing on these factors alongside potential harm, we can better design interventions that are well-targeted and efficient in curbing financial misconduct.

Funding

The research was supported by Czech Science Foundation Project No. 19-10781S. The funder had no role in study design, data collection and analysis, or preparation of the manuscript.

CRediT authorship contribution statement

Štěpán Bahník: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. **Marek Vranka:** Methodology, Investigation, Writing – review & editing.

Declaration of Competing Interest

None.

Data availability

All data generated and analyzed in this study are available at https://osf.io/pqzyr/

Acknowledgements

We would like to thank Radka Francová, Kateřina Hudáčová, Martin Máčel, Nicolas Say, and Jáchym Vintr for testing web applications used for data collection. We are also thankful to Puneet Arora for insightful comments on the draft of the manuscript.

References

Abbink, K., Irlenbusch, B., Renner, E., 2002. An experimental bribery game. J. Law Econ. Organiz. 18 (2), 428–454.
Abbink, K., Serra, D., 2012. Anticorruption policies: lessons from the lab. Newadvances in Experimental Research On Corruption. Emerald Group Publishing Limited.
Bahník, Š., Vranka, M.A., 2022a. Experimental test of the effects of punishment probability and size on the decision to take a bribe. J. Behav. Experim. Econ. 97, 101813.
Bahník, Š., Vranka, M., 2022b. No evidence of moral licensing in a laboratory bribe-taking task. Sci. Rep. 12 (1), 1–7.
Barr, A., Serra, D., 2009. The effects of externalities and framing on bribery in a petty corruption experiment. Experim. Econ. 12 (4), 488–503.
Becker, G.S., 1968. Crime and punishment: an economic approach. J. Polit. Econ. 76 (2), 169–217.
Broadstock, D., Chen, X., 2021. Corporate site visits, private monitoring and fraud: evidence from China. Finance Res. Lett. 40, 101780.
Cameron, L., Chaudhuri, A., Erkal, N., Gangadharan, L., 2009. Propensities to engage in and punish corrupt behavior: experimental evidence from Australia, India, Indonesia and Singapore. J. Public Econ. 93 (7–8), 843–851.
Celse, J., Max, S., Steinel, W., Soraperra, I., Shalvi, S., 2019. Uncertain lies: how payoff uncertainty affects dishonesty. J. Econ. Psychol. 71, 117–125.
Cumming, D., Johan, S., Peter, R., 2018. Developments in financial institutions, governance, agency costs, and misconduct. J. Int. Financ. Markets Instit. Money 54, 1–14.
Dana, J., Weber, R.A., Kuang, J.X., 2007. Exploiting moral wiggle room: experiments demonstrating an illusory preference for fairness. Econ. Theory 33 (1), 67–80.
Desvousges, W.H., Johnson, F.R., Dunford, R.W., Boyle, K.J., Hudson, S.P., Wilson, K.N., 2010. Measuring Nonuse Damages Using Contingent valuation: An experimental Evaluation of Accuracy. RTI press.
Dickert, S., Västfjäll, D., Kleber, J., Slovic, P., 2015. Scope insensitivity: the limits of intuitive valuation of human lives in public policy. J. Appl. Res. Mem. Cogn. 4 (3), 248–255.
Erev, I., Roth, A.E., 2014. Maximization, learning, and economic behavior. Proc. Natl Acad. Sci. 111, 10818–10825. Supplement 3.
Friesen, L., 2012. Certainty of punishment versus severity of punishment: an experimental investigation. South. Econ. J. 79 (2), 399–421.
Gerlach, P., Teodorescu, K., Hertwig, R., 2019. The truth about lies: a meta-analysis on dishonest behavior. Psychol. Bull. 145 (1), 1–44.
Gomila, R., 2021. Estimating causal effects of experimental treatments on binary outcomes using regression analysis. J. Experim. Psychol. Gen. 150 (4), 700–709.
Guerra, A., Zhuravleva, T., 2019. Social norms in corruption: a bribery experiment. EUI MWP, 2019/07Available at. http://hdl.handle.net/1814/63589.
Hauser, M., Cushman, F., Young, L., Kang-Xing Jin, R., Mikhail, J., 2007. A dissociation between moral judgments and justifications. Mind Lang. 22 (1), 1–21.
Houdek, P., 2019. Is behavioral ethics ready for giving business and policy advice? J. Manage. Inquiry 28 (1), 48–56.
Köbis, N.C., Verschuere, B., Bereby-Meyer, Y., Rand, D., Shalvi, S., 2019. Intuitive honesty versus dishonesty: meta-analytic evidence. Persp. Psychol. Sci. 14 (5), 778–796.
Laske, K., Saccardo, S., Gneezy, U., 2018. Do fines deter unethical behavior? The effect of systematically varying the size and probability of punishment. Available at SSRN. https://ssrn.com/abstract=3157387.
Leib, M., Köbis, N., Soraperra, I., Weisel, O., Shalvi, S., 2021. Collaborative dishonesty: a meta-analytic review. Psychol. Bull. 147 (12), 1241–1268.
Nagin, D.S., 2013. Deterrence in the twenty-first century. Crime Justice 42, 199–263.
Rahimi, L.R. (2020). Public Policy and Corruption: experimental Evidence. Available online at: https://ore.exeter.ac.uk/repository/handle/10871/124130.
Reurink, A., 2019. Financial fraud: a literature review. Contemp. Topics Finance Collect. Literat. Surveys 79–115.
Schad, D.J., Vasishth, S., Hohenstein, S., Kliegl, R., 2020. How to capitalize on a priori contrasts in linear (mixed) models: a tutorial. J. Mem. Lang. 110, 104038.
Schulte-Mecklenbeck, M., Johnson, J.G., Böckenholt, U., Goldstein, D.G., Russo, J.E., Willemsen, M.C., 2017. Process-tracing methods in decision making: on growing up in the 70s. Curr. Dir. Psychol. Sci. 26 (5), 442–450.
Slovic, P., 1987. Perception of risk. Science 236 (4799), 280–285.
Soltes, E., 2019. The frequency of corporate misconduct: public enforcement versus private reality. J. Financ. Crime 26 (4), 923–937.
Thielmann, I., Hilbig, B.E., 2019. No gain without pain: the psychological costs of dishonesty. J. Econ. Psychol. 71, 126–137.
Teodorescu, K., Plonsky, O., Ayal, S., Barkan, R., 2021. Frequency of enforcement is more important than the severity of punishment in reducing violation behaviors. Proc. Natl Acad. Sci. 118 (42), e2108507118.
Tversky, A., Kahneman, D., 1992. Advances in prospect theory: cumulative representation of uncertainty. J. Risk Uncertain. 5 (4), 297–323.
Vranka, M.A., Bahník, Š., 2018. Predictors of bribe-taking: the role of bribe size and personality. Front. Psychol. 9, 1511.
Xiong, J., Ouyang, C., Tong, J.Y., Zhang, F.F., 2021. Fraud commitment in a smaller world: evidence from a natural experiment. J. Corp. Finance 70, 102090.