Individual Level Evidence of Dishonesty and the Gender Effect

Lana Friesen and Lata Gangadharan*

Abstract
We study dishonesty in an individual task experiment. In contrast to the existing literature, we collect participant level data. We find that men are not only more likely to be dishonest than women, they are also more dishonest.

Keywords: dishonesty, individual decision making, experiment, gender.
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1. Introduction

While studying dishonesty in laboratory settings has become increasingly popular, evidence on dishonesty in individual decision-making tasks in contexts other than tax compliance is scarce as most of the existing experimental economics literature on dishonesty uses two-player communication games. Individual tasks are particularly important for understanding certain types of dishonesty such as “white collar” crimes where the party harmed by the dishonesty may be distant from, and possibly unknown to, the decision maker. While Mazar et al. (2008), Fischbacher and Heusi (2008), and Hauser et al. (2010) use individual tasks, they only observe dishonesty at the aggregate level, as they do not collect individual level data on dishonesty.

We use the same experimental task as Mazar et al. (2008) but in contrast collect individual level data on dishonesty. By doing so, we observe not only the actual distribution of dishonesty but can build a profile of those most likely to be dishonest by linking behavior to demographic factors. The results reveal that one-third of participants are dishonest, and one-quarter to the maximum degree possible. We also add depth to the existing literature on gender differences in dishonesty (Dreber and Johannesson, 2008; Childs, 2012) by finding that men are not only more likely to be dishonest than women, but they are also likely to be more dishonest (around twice as much). The characteristics of dishonest men and women differed with dishonest men more likely to be older, locally born, and influenced by economic incentives, while dishonest women were not risk averse. To the best of our knowledge, this is one of the first studies to link individual level data on dishonesty to demographic factors in a context other than tax compliance.²

2. Experimental Design

1 See Ellingsen and Johannesson (2004), Gneezy (2005), and the following literature. Alm et al. (2009) is a recent example of the large experimental tax compliance literature.
2 Demographic factors have been studied in tax compliance experiments, e.g. Alm et al. (2009).
To measure dishonesty in an individual task we used the matrix task of Mazar et al. (2008). In contrast however, we collected individual data, rather than having subjects recycle or shred the task sheets. The task involves finding a pair of numbers that adds up to exactly 10.00 from a matrix of 12 three-digit numbers (e.g. 5.34). Subjects were given a sheet of 20 matrices, five minutes to solve as many as possible, and instructed that they would earn $1 for each correctly solved matrix.

To collect individual data we used the following procedure. After the five minutes, subjects were instructed to record the number of correctly solved matrices on their collection slip. We then collected the folded matrix sheets and placed them in a sealed envelope, emphasizing that we would not open the envelope until everyone had left the lab. Subjects were instructed to pay themselves for the task from a small envelope containing 20 $1 coins that was already placed on their desk before the experiment, place their completed collection slip and any remaining money in the small envelope, seal it, and leave it on their desk for us to collect after everyone had left the lab.\(^3\)

Several features of the design are worth emphasizing. First, in order to ensure there was considerable scope for cheating even for top performers - not all of the matrices have solutions, of which subjects were aware. The incentive to cheat ranged from $10, for anyone who solved all ten matrices that had solutions, to $20 for someone who solved none. Second, subjects can readily evaluate their own performance so any dishonest gain can be reasonably interpreted as cheating, rather than as a genuine mistake.

The experiment was held at the University of Queensland with 115 participants. The task lasted 10 minutes, with average earnings of AU$7 (approximately US$6.50). The task was embedded in a longer experiment and followed a computerized risk elicitation task involving ten lottery choices. Earnings from the risk task were not computed until the end of

\(^3\) We therefore conveyed that the probability of detection was zero, which it was.
the entire session. Following the matrix task, instructions were distributed for a separate production and reporting task (reported in Friesen and Gangadharan, 2012). Demographic and attitude variables were collected in a final questionnaire.

3. Results

As subjects can readily evaluate their own performance, we describe anyone who took more money than they were entitled to as dishonest. Subjects correctly solved 4.5 matrices on average, with only two able to solve all ten, and six solving none. On average, subjects took $2.43 more than they were entitled to, considerably below the maximum dishonest gain possible, which was $15.48 on average and ranged from $10 to $20.\(^4\)

Using this interpretation of dishonesty, we construct several measures of dishonesty. The first is a simple indicator of whether or not a subject took extra money, with one-third of the subjects meeting this criterion. Second, we measure the magnitude of dishonesty by how much extra money they took. Of the 38 dishonest subjects, 37% kept one dollar extra, 42% ten dollars extra, and 18% kept fifteen dollars or more. We also computed a subject’s dishonest gain as a percentage of their maximum dishonest gain possible, given their number of correctly solved matrices. We found that one-quarter (26%) of the dishonest took the maximum amount possible.

Disaggregating the data by gender, we find that men are more likely to be dishonest. The difference is substantial but is marginally insignificant (24.4% of women are dishonest vs. 38.6% of men; p-value from a Mann-Whitney test = 0.11). Moreover men are dishonest by a larger amount, taking on average 21% of the maximum possible compared with only 7% for women (p-value = 0.05). Men also take more when they are dishonest with dishonest women taking 28% of the maximum possible while dishonest men take 54% of the maximum

\(^4\) The maximum possible dishonest gain equals $20 minus the number of correctly solved matrices.
possible (p-value =0.06). This is even more striking when we examine the gender composition of those who took the maximum possible, as only one of these ten subjects was female. As a proportion of the sample size this gender difference is significant (2% of females vs. 13% of males, p-value = 0.05).

Figure 1 illustrates these gender differences, where the size of the circles reflects the number of observations at each point. The larger circles along the diagonal indicate that most subjects were honest, with circles above the diagonal showing that some subjects took more money than they had earned. These circles are more frequent for men, and both low and high performers in the male sample seem to be equally dishonest. Women in contrast are rarely dishonest.

To link dishonest behaviour with demographic factors, we report in Table 1 the results from Tobit regression models where the dependent variable is the extra money taken as a percentage of maximum dishonest gain possible. Independent variables include gender, age, area of study, place of birth, a measure of risk preferences (Risk Averse: constructed from the lottery choice task), and an attitude variable that indicates agreement with the statement, “I am more inclined to lie, the more I have to gain from the lie”.

Model 1 confirms our earlier results, with males dishonest by a significantly larger magnitude than females. In addition, the magnitude of dishonesty was significantly greater for older and locally born subjects, as well as those who reported that it was acceptable to lie if the gain from lying is higher.\(^5\)

Models 2 and 3 show separate regressions for men and women, and demonstrate that the men in the sample drove the demographic patterns in the data, with greater dishonesty among older and locally born men and those influenced by monetary gains.\(^6\) In contrast, women are influenced by risk preferences, with risk averse female subjects taking less

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\(^5\) Alternative models, such as using the absolute magnitude of dishonesty yield similar results.

\(^6\) Kuhn and Villeval (2011) also find men to be more responsive to financial incentives than women in the context of team production.
money. Business/economics subjects took less money in the female sample, although this is only marginally significant (p-value = 0.10).

4. Discussion

By collecting individual level data on dishonesty, we were able to examine the true distribution of dishonesty, and identify the demographic characteristics of those who are more likely to be dishonest. We find that only one-third of subjects were dishonest, some to the maximum extent possible, a result that contrasts with the conclusion of Mazar et al. (2008) that nearly everyone is dishonest to a small degree. Mazar et al. (2008) however did not observe the distribution of dishonesty and based their conclusion on the observation of less than maximal cheating in the aggregate data.

We also extend the existing literature on gender differences in dishonest behavior, previously observed in two-player communication games (Dreber and Johannesson, 2008; Childs, 2012) and income tax compliance experiments (e.g. Alm et al. 2009). As in this previous literature, we find that men are more likely to be dishonest, but our design enables us to investigate differences in the magnitude of this dishonesty. We find that men are not only more likely to be dishonest, but to cheat by a larger amount when they are dishonest. Further, the characteristics of dishonest men and women are different, reflecting that men and women are motivated and influenced by different factors.

Understanding the determinants of dishonesty has important implications for reducing fraud. This paper takes the first step in this direction. These insights can enable policies to be specifically tailored to the appropriate context and group (British Cabinet Office, 2012).
Table 1: Tobit Model of Magnitude of Dishonesty

<table>
<thead>
<tr>
<th>Dependent Variable: Percent of Maximum Dishonest Gain</th>
<th>(1) Full Sample</th>
<th>(2) Men</th>
<th>(3) Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>0.468**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.211)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business or Economics Major</td>
<td>0.029</td>
<td>0.207</td>
<td>-0.343*</td>
</tr>
<tr>
<td></td>
<td>(0.195)</td>
<td>(0.271)</td>
<td>(0.203)</td>
</tr>
<tr>
<td>Age</td>
<td>0.149***</td>
<td>0.184**</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.083)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Risk Averse</td>
<td>-0.210</td>
<td>0.046</td>
<td>-0.520**</td>
</tr>
<tr>
<td></td>
<td>(0.225)</td>
<td>(0.320)</td>
<td>(0.234)</td>
</tr>
<tr>
<td>More Likely to Lie if Gain Large</td>
<td>0.382***</td>
<td>0.453***</td>
<td>0.134</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.158)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Born in Australia or NZ</td>
<td>0.531**</td>
<td>0.734**</td>
<td>0.143</td>
</tr>
<tr>
<td></td>
<td>(0.224)</td>
<td>(0.331)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.771***</td>
<td>-5.631***</td>
<td>-1.030</td>
</tr>
<tr>
<td></td>
<td>(1.297)</td>
<td>(1.981)</td>
<td>(1.113)</td>
</tr>
<tr>
<td>Observations</td>
<td>115</td>
<td>70</td>
<td>45</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10
Figure 1: Distribution of Magnitude of Dishonesty by Gender

Graphs by male
Acknowledgments: We thank the University of Queensland for funding, and Nina Mazar for sharing her matrix task

References


Cabinet Office Behavioural Insights Team, 2012. Applying behavioural insights to reduce fraud, error and debt. U.K.


