

Dishonesty and Selection into Public Service in Denmark: Who Runs the World's Least Corrupt Public Sector?*

Sebastian Barfort[†]

Nikolaj Harmon[‡]

Frederik Hjorth[§]

Asmus Leth Olsen[¶]

September 4, 2015

Abstract

Are country-level differences in corruption related to the dishonesty level of individuals entering public service? Recent studies have found that dishonest individuals self-select into public service in high-corruption settings. Little is known, however, about what is driving this pattern and whether a similar pattern exists in low-corruption settings. This paper examines selection into public service in the world's least corrupt country, Denmark. We subject a relevant student population to a standard experimental dishonesty task and develop a novel method to estimate individual-level dishonesty from the experimental data. We then relate estimates of dishonesty to subjects' job preferences and characteristics. In contrast to previous findings, dishonest individuals in low-corruption Denmark are *less* likely to want to enter public service. This self-selection is not related to risk-aversion or ability. Instead, we find that dishonest individuals who self-select into higher paid private sector careers such as finance are less altruistic and place a higher weight on their own earning opportunities. Accordingly, counterfactual wage questions suggest that higher public sector wages would attract *more* dishonest candidates to the public sector in Denmark.

*This research was funded by a grant from the Faculty of Social Sciences at the University of Copenhagen, Denmark. We thank Andreas Gotfredsen, Ray Fisman, Rema Hanna, Marco Piovesan, Søren Serritzlew, Peter Bjerre Mortensen, David Broockman, Robert Klemmensen, Alexander Sebald and numerous seminar participants for helpful comments and discussions. Previous versions of the paper was presented at: The Midwest Political Association Meeting, Chicago, April 16th, 2015, The Public Management Research Conferences, Minneapolis, June 13th, 2015, Stockholm University SOFI, University of Copenhagen, Aarhus University, and Copenhagen Business School.

[†]Sebastian Barfort is a Ph.D. candidate in economics at University of Copenhagen (sebastian.barfort@econ.ku.dk).

[‡]Nikolaj A. Harmon, Department of Economics, University of Copenhagen (nikolaj.harmon@econ.ku.dk).

[§]Frederik Hjorth is a Ph.D. candidate in political science at University of Copenhagen (fh@ifs.ku.dk).

[¶]Asmus Leth Olsen, Department of Political Science, University of Copenhagen (ajlo@ifs.ku.dk).

1 Introduction

Corruption, understood as the misuse of public office for private gain, imposes enormous economic and social costs on societies. Yet the costs of corruption are unequally distributed. In some countries, corrupt behavior is an endemic feature of public life. In others it is nearly non-existent. Existing research on corruption has tended to emphasize how differences in the formal incentives for corruption shape individuals' decisions about engaging in corrupt behavior. While this focus has been very fruitful (see Olken and Pande 2012 for a recent survey), recent evidence also suggests that differences in the formal individual incentives for corruption may not tell the whole story. Fisman et al. (forthcoming) and Fisman and Miguel (2007), for example, have shown that in international organizations consisting of politicians and public officials from many different countries, individuals from high-corruption countries exhibit more corrupt behavior than their low-corruption colleagues despite facing the same formal incentives and institutional environment.

This paper deals with a different, complementary explanation for the observed differences in corruption levels; namely that corruption levels may be influenced by the selection of more or less dishonest individuals into public service. This explanation builds on two basic premises. First, there is growing evidence that individuals differ in their inherent propensity to engage in dishonest behavior (e.g. Fischbacher and Föllmi-Heusi 2013; Arbel et al. 2014; Hilbig and Zettler 2015). Viewing corruption as a type of dishonest behavior, a public sector populated by inherently dishonest individuals should therefore exhibit higher levels of corruption than one populated by honest ones. Second, there is good reason to suspect that selection patterns into public service may differ across countries. The characteristics of public service vis-à-vis private sector jobs may differ and attract different types of individuals in different countries. Moreover, the mere fact that corruption is more prevalent in some countries may in itself make dishonest individuals more likely to want to enter into public service in these countries.

That dishonesty and selection may matter for corruption has received nascent empirical support in recent experimental studies by Hanna and Wang (2013) and Banerjee, Baul, and Rosenblat (2015). In their experiment on dishonesty, Hanna and Wang (2013) find that in India, dishonest university students are more likely to want to enter public service. Conducting a

corruption experiment at two different Indian universities, Banerjee, Baul, and Rosenblat (2015) also find more dishonest behavior at the university targeting public service careers. These findings from high-corruption India, however, beg the question of what the selection of honest and dishonest individuals into public service looks like in low-corruption settings. If a similar selection pattern holds in low-corruption settings, then differences in selection into public service can not explain differences in corruption between countries. Conversely, if low corruption levels in some countries are indeed underpinned by a very different pattern of selection into public service, it becomes of key interest to understand what determines the pattern of self-selection into public service in low-corruption settings and whether this pattern might be affected by policy.

In this paper we take the first steps towards answering these questions by studying dishonesty and selection into public service in what is typically viewed as the world's least corrupt country, Denmark. Following Hanna and Wang (2013), we subject a relevant population of Danish students to a standard set of experimental cheating tasks building on Fischbacher and Föllmi-Heusi (2013) and Jiang (2013). In our implementation of the task, students can win money by correctly guessing the outcome of a series of dice rolls but are allowed to see the outcome of each roll before reporting their guess. Students therefore have the option of winning dishonestly by misreporting their guess, knowing that it can never be proven whether in fact they were dishonest. Comparing the distribution of successful guesses of the dice game to the expected distribution without lying, however, is informative about dishonest behavior. We develop and apply a novel statistical framework that allows us to both estimate individual propensities for dishonesty, as well as the full distribution of dishonesty across the student population. After obtaining individual estimates of students' propensities for dishonesty, we then relate these to survey responses regarding job preferences, as well as observable respondent characteristics and behavior in other standard experimental tasks.

The paper's main results are that in low-corruption Denmark, dishonesty differs markedly across individuals and is negatively related to preferences for public service. In the empirical analysis, we first document extensive heterogeneity in the propensity for dishonesty among Danish students. While 10 % of students barely cheat at all, 13 % cheat practically all the time. The remaining 77 % fall somewhere in-between, resulting in a standard deviation of cheat rates

across students of 0.39. Second, in sharp contrast to the previous evidence from highly-corrupt India, we show that dishonest individuals in Denmark are systematically *less* likely to want to enter public service. Students ranking public administration as one of their top two job choices cheat around 10 percentage points less than other students. This pattern is present across a wide range of job preference measures.

Next, we shed light on what underpins this selection pattern in Denmark by examining how dishonesty and job preferences are related to other subject characteristics. We focus here on four possible determinants of dishonesty and job preferences: Risk-aversion, ability, altruism and gender. We find no evidence that ability or risk-aversion plays a role in shaping the self-selection of honest individual into public service. In particular, dishonesty does not correlate with grades, experimental measures of risk aversion, or stated preferences for job security. Conversely, we find a clear role for altruism and relative valuation of earnings. Students who donate less in a dictator game and state that salary is an important job characteristic are both more dishonest and more likely to prefer private sector jobs. Moreover, dishonest students are particularly likely to express a preference for high-paying financial sector jobs. We also find that men are more likely to be dishonest than women and are less likely to want to work in the public sector, although this pattern largely appears to be working through gender differences in altruism and valuation of own earnings.

Finally, we examine the effect of increasing public sector wages on selection into public service in Denmark. Higher public sector wages are often cited as a way to combat corruption. If dishonest individuals are self-selecting out of the public sector in part due to its relatively low wage, however, higher public sector wages may *increase* the dishonesty level of public service candidates. We confirm this prediction in our data by analyzing a set of counterfactual job preference question that vary the public-private wage gap. As the relative wage of public sector jobs are increased, the average dishonesty among students preferring public sector jobs increases.

Overall, our results suggest that differences in the dishonesty level of people who self-select into public service may play an important part in explaining differences in corruption across countries, particularly when contrasted with the previous results from high-corruption India

(Hanna and Wang 2013; Banerjee, Baul, and Rosenblat 2015). Moreover, our results regarding the effect of higher public sector wages highlight the importance of better understanding selection into public service in the dishonesty dimension and how this selection is affected by various policies.

In terms of previous work, the idea that individuals may differ in their inherent propensity for dishonesty and corrupt behavior has a long tradition in the theoretical literature on corruption (Lui 1986; Cadot 1987; Andvig and Moene 1990) and is supported empirically by the fact that inherent personality traits predict corrupt behavior (Callen et al. 2015). That selection in the dishonesty dimension may be important has also received some theoretical attention (Caselli and Morelli 2004; Besley 2004; Bernheim and Kartik 2014).

On the empirical side, a number of recent papers have examined the issue of selection into public service.¹ Selection patterns in terms of dishonesty, however, have garnered little attention outside the India studies of Hanna and Wang (2013) and Banerjee, Baul, and Rosenblat (2015). At the individual level, Alatas et al. (2009) find no correlation between bribing behavior in an explicit corruption game and stated preferences for working in the public sector among Indonesian students. At the aggregate level Dollar, Fisman, and Gatti (2001) report that low-corruption countries have more female representation in parliament and interprets this as stemming from gender differences in dishonesty that dovetail our results regarding gender.

Relative to this existing literature, our paper contributes by being the first paper to examine the link between dishonesty and selection into public service in a low-corruption setting and by providing evidence on how this link is related to other characteristics and the level of public sector wages.

Methodologically, we also both draw on and contribute to a growing economics literature on dishonesty. Besides Fischbacher and Föllmi-Heusi (2013) and Hanna and Wang (2013), our experimental dishonesty task draws particularly on Jiang (2013). We in turn contribute to this literature by developing a novel statistical framework that makes it possible to estimate the full

¹Dal Bó, Finan, and Rossi (2013), Ashraf et al. (2014), and Deserranno (2014) use field experiments to examine how pecuniary incentives affects selection into public service jobs in Mexico, Zambia and Uganda in various dimensions, including ability and pro-social preferences. Combining survey and experimental data, Kolstad and Lindkvist (2012) and Serra, Serneels, and Barr (2011), document that pro-social preferences correlate with wanting to work in the public sector in Tanzania and with working in the non-profit sector in Ethiopia.

distribution of individual dishonesty and examine the statistical implications of various features of the experimental design, including the number of times the task is repeated by subjects.²

The paper proceeds as follows. In Section 2, we outline key characteristics of Denmark and the student population we study. In Section 3 we present the survey experiment used to construct the key variables of the study, dishonesty and preference for public sector employment. In Section 4 we present the empirical results. Section 5 concludes.

2 Empirical setting

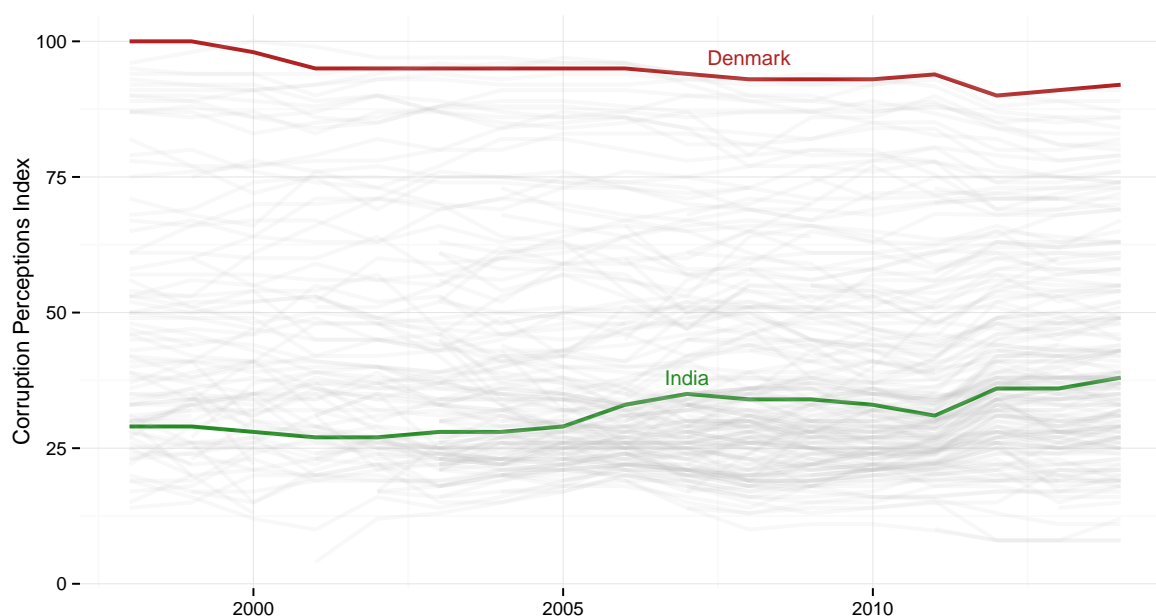
The setting of the study is Denmark. For understanding how dishonesty and selection into the public sector relates to corruption, Denmark is particularly interesting as a low-corruption benchmark because of its consistent ranking among the least corrupt countries in the world. Figure 1 shows the levels of corruption in different countries 1996-2014 as measured by the Transparency International's Corruption Perceptions Index (CPI), with Denmark and India highlighted. Denmark has ranked as the least corrupt country in the CPI every year but one, and in the history of the CPI has never ranked lower than fourth. This pattern is not exclusive to the CPI. For example, the World Bank Governance Indicator "Control of Corruption", detailed in Kaufmann, Kraay, and Mastruzzi (2010), has ranked Denmark as the least corrupt country in the world every year since 2007 and never ranked Denmark lower than second.³

As noted in the introduction, the previous evidence on dishonesty and selection in Hanna and Wang (2013) and Banerjee, Baul, and Rosenblat (2015) come from India, which is generally perceived to have a relatively corrupt public sector. As Figure 1 shows, India has consistently been in the bottom half of the 50 to 180 countries included in the CPI between 1996-2014 and currently ranks as number 85 out of 175. Contrasting the patterns of dishonesty and selection into

²Our paper has broader methodological ties to two other strands of literature. By using experimental methods to study questions related to corruption, our paper relates to a bigger experimental literature on corruption or bribery games. This literature differs from our paper, however, by examining games where subjects can engage in bribing or other corrupt behavior and by primarily focusing on the effects of institutional settings such as various forms of monitoring (see Abbink and Serra 2012 for a recent survey). Additionally, by using experimental methods to examine selection into public service careers, our paper also relates to recent work using experimentally-measured worker characteristics to study sorting in the labor market (e.g. Dohmen and Falk 2011; Fouarge, Kriechel, and Dohmen 2014; Cohn, Fehr, and Maréchal 2014).

³Beyond corruption rankings, national representative surveys of citizens' perceived trustworthiness of various institutions and occupational groups find a persistent pattern of high levels of trust in the political system, the public sector and its employees (see Sønderskov and Dinesen 2014).

Figure 1: Corruption Perceptions Indices 1996-2014, all countries



The figure shows the evolution of the Corruption Perceptions Index (CPI) 1996-2014 for all countries in the CPI data (grey), with Denmark and India highlighted.

public service in Denmark with the previous results from India will therefore provide valuable evidence on how such selection is related to country-level differences in corruption.

Within Denmark, the population we study are students enrolling as undergraduates in the fields of law, economics and political science. In the Danish higher education system, students choose a field of study already upon entering university. Conditional on not dropping out, practically everyone continues to do a masters degree in the same field of study. The students enrolling in one of these three fields therefore generally graduate with a masters degree about five to seven years after enrolling in the undergraduate degree.

We chose to focus on this student population for two reasons: The first reason is that this population faces a very clear choice between entering the private sector or going into public service. For current employees with a background in economics, law, or political science, around 46 percent work in the public sector and 54 in the private sector. Typical private sector careers for this student population include finance, law firms, and lobbying organizations. In terms of public service careers, the vast majority goes into some form of public administration.

The second reason we focus on this student population is that it is large and important enough

to actually affect the corruption level of the public sector. About 10 percent of all state level employees have a background in one of the three fields we study. They are also dominant at the very top-level of the public sector: 100 pct. of current permanent secretaries and about 40 pct. of members of parliament hold a degree in one of the three fields.

As discussed above, corruption is by all accounts very rare in Denmark. Given the motivation for our study, however, it is worth briefly considering what type of corrupt behavior our student population might in principle undertake in their public service careers. For those entering public administration at the local level, many of them will be engaged in direct administrative decisions that affect individual citizens. Examples include decisions on various permits, building regulations, business licenses, divorce cases, adoption, and paternity issues. Private citizens or local businesses with interests in cases of this type could attempt to bribe the responsible public official. In other instances, potential corruption could take a more indirect form. Many graduates from these fields work in offices which help develop and prepare legislation or policy input to elected officials. Organized interests or private companies could aim to bribe lower level bureaucrats in order to affect the outcome of these policy processes.

3 Data and experimental design

Our empirical analysis is based on an online survey experiment conducted at the University of Copenhagen during December 2014.⁴ The university administration provided us with complete lists of everyone who enrolled as undergraduates in law, economics and political science, including student e-mail addresses. From these lists a random sample of students who enrolled over the years 2009-2011 and 2013-2014⁵ was drawn from each of the three fields and these samples were invited to participate in the survey experiment.

The invitation to participate was sent as an e-mail with a link to the survey along with a username and password. Participants were told that the survey dealt with their attitudes to various

⁴The experiment was run using a software called “ILab” developed by Andreas Gotfredsen and Alexander Sebald from the Economics Department at the University of Copenhagen designed to conduct large scale internet experiments.

⁵Students who enrolled prior to 2009 were not invited as many of them will have already graduated by 2013 and therefore may no longer use their student e-mail addresses. Pilot studies and technical tests were run on students enrolling in 2012, so these were not invited so as to not contaminate the subject pool.

topics and “how they acted in situations characterized by uncertainty.” The latter referred to the various incentivized games which they would encounter in the survey and which will be outlined in detail below. Participants were also told that they would be paid to participate. In accordance with the actual outcomes, participants were informed that the average participant would earn no less than 50 DKK (8 USD),⁶ that the maximum payoff was above 300 DKK (50 USD), and that the survey would take approximately 20 minutes to complete.⁷ For comparison, the student population in question would in a typical student job usually receive a union defined hourly wage of about 110 DKK (18 USD), corresponding to 37 DKK (6 USD) per 20 minutes. The announced (and realized) payoffs therefore made participation attractive without being excessively high. In addition to the initial invitation e-mail, two follow-up reminder e-mails were also sent after six and 17 days.

In the end, 863 subjects completed the survey. From these we drop one individual who experienced technical difficulties during the main dishonesty experiment in the survey, leaving us with a base sample of 862 participants. In terms of representativeness, our sampling scheme ensures that the sample receiving e-mail invitations is representative of our population of study. At the end of Section 4 and in the appendix, we further examine potential issues related to selective non-participation by exploiting the availability of administrative university data for non-participants.

3.1 Experimental dishonesty game

The first main purpose of our survey experiment is to measure individual subjects’ inherent propensity for dishonesty. We follow Hanna and Wang (2013) and measure dishonesty using a repeated version of the dice game approach from Fischbacher and Föllmi-Heusi (2013) (referred to as *dice-under-cup* from now on). Behavior in various types of dice-under-cup games have become a widely used measure of dishonesty (for recent examples see Cohn, Maréchal, and Noll (2015), Cohn, Fehr, and Maréchal (2014), Ariely et al. (2014) or Shalvi, Eldar, and Bereby-Meyer (2012)). Behavior in dice-under-cup games have been shown correlate with real world dishonest

⁶At the time of the survey experiment 1 DKK equaled about 6 USD.

⁷The maximum payoff among participants was 315 DKK (53 USD), while the average payoff was 80 DKK (13 USD). The median time from first opening the survey to completion was 25 minutes, although since participants were free to leave the survey and come back later to finish this likely overstates actual time use.

behavior and rule breaking (Hanna and Wang 2013; Cohn, Maréchal, and Noll 2015).⁸

We adapted the implementation of the game to our empirical setting and statistical framework. In particular, to be able to systematically examine and address issues of sample representativeness and non-participation, we used an online version of the game based on the computer-adaptation in Jiang (2013) and used university records to sample and recruit students via e-mail. The online implementation also allows us to obtain a larger sample than would have been practical in a lab implementation.

Our implementation of the dice-under-cup game proceeded in the following way:⁹ At four different points in the survey experiment, participants were asked to play ten rounds of a dice game. Students were told that the game was intended to test how they “guess in situations characterized by randomness” and that they could win money in the game by correctly guessing the outcome of a dice roll. In each round of the dice game subjects were first asked to think of a number between 1 and 6 that they expected the dice to show after the dice roll. Students then clicked “next” while keeping their guess in mind. A dice was rolled on screen and the outcome of the dice roll was reported. The participants were then asked to report their guess while the actual outcome of the dice roll was still displayed. On the following screen the payoff from the round was reported. Reporting a correct guess yielded a gain of 2 DKK (0.33 USD) relative to an incorrect one.¹⁰

The point of the dice-under-cup game is that in each round, subjects have the option of winning dishonestly by reporting the actual outcome of the dice roll regardless of what their initial guess was. Moreover, a strength of the design is that subjects are not explicitly primed to think about dishonesty and subjects know in each round that it can never be revealed whether in fact they reported their guess honestly.¹¹ Comparing the number of successful guesses across

⁸Given that the present paper is motivated by understanding public sector corruption, the validation exercise in Hanna and Wang (2013) is particularly relevant. Hanna and Wang (2013) show that dishonesty in a dice-under-cup game is correlated with fraudulent absenteeism in a sample of public sector nurses.

⁹A screen cap of the game as viewed by the subjects are presented in the appendix including exact translations of all instructions for the game.

¹⁰Depending on the round a correct guess either yielded 3 DKK or 2 DKK, while an incorrect one either yielded 1 DKK or 0 DKK so as to keep the gain from a correct guess constant equal to 2 DKK. The change in payoffs across the different rounds was used to achieve a suitable level for the total (expected payoff), while avoiding decimals payoff amounts. In our pilot studies, we found no evidence that such changes in the levels of payoffs affected behavior in the dice game.

¹¹One may still worry that upon realizing that they can lie undetected in the game, subjects implicitly feel that being dishonest is the point of the game. In an attempt to mitigate this type of experimental demand, we concluded

the forty rounds of the dice game to the expected distribution of successful guesses, however, is informative about dishonest behavior. The next section presents the statistical framework we use to estimate individual propensities for dishonesty from the experimental results.

3.2 Measuring dishonesty

We now present the simple statistical framework that we use to construct estimates of the distribution and individual levels of dishonesty from subjects' behavior in the dice-under-cup game described above.

The data consists of a random sample of N subjects, which we index by i . Each subject participates in a series of K rounds of a dice-under-cup game, which we index by k . As described above, our experiment and data has $N = 862$ and $K = 40$. In each round the subject can either win or lose. The rounds are independent of each other with a constant probability of winning of p^* . In our experiment the probability of (truthfully) guessing a dice roll is one in six so $p^* = \frac{1}{6}$ in our case.

In the dice-under-cup game, we do not directly observe whether subjects win or lose, however. For each round and each subject, we instead observe a self-reported measure of whether the subject won or not, where subjects are free to report dishonestly. We let y_{ik} be an indicator variable for whether subject i reported winning in round k . In the context of our implementation of the dice-under-cup game, y_{ik} is simply an indicator for whether the reported guess matches the actual dice roll. We let $Y_i = \sum_{k=1}^K y_{ik}$ denote the total number of wins (total number of correct guesses) reported by subject i .

We introduce heterogeneity in the propensity for being dishonest by assuming that when reporting the outcome of a round, subject i reports dishonestly some fraction $\theta_i \in [0, 1]$ of the time. We further make the assumption that if reporting dishonestly, a subject reports a win for sure in that round. Otherwise he or she reports the truth. The subject-specific θ_i therefore captures subject i 's propensity for dishonesty and we refer to it as subject i 's *cheat rate*. Thus the aim of our empirical analysis will be to first examine the extent of heterogeneity in subjects' cheat rates and second how cheat rates relate to job preferences and other characteristics.

the introduction screen by stating that: "it is important that you are careful about remembering and reporting the exact number on which you guessed prior to rolling the die."

Perhaps the most obvious way of examining heterogeneity in dishonesty from the repeated dice-under-cup game would be to simply examine the heterogeneity in the number of wins reported across subjects. Doing so, however, confounds differences in the level of dishonest behavior with differences in the amount luck experienced in the dice game. We therefore take a different approach that allow us to separate true heterogeneity in dishonesty from differences in luck. In the appendix, we show how a flexible maximum likelihood estimator for the full distribution of cheat rates can be constructed under simple assumptions on the time dependence of dishonest behavior. In our empirical analysis, we use this approach to examine the underlying heterogeneity in dishonesty.

Next, in order to examine the relationship between cheat rates, job preferences and other characteristics, we construct individual measures of each subject's cheat rate. The probability of observing a win for a subject with a given cheat rate, θ_i , is $P(Y_{ik} = 1|\theta_i) = p^* + (1 - p^*)\theta_i$. As a result, a simple transformation of a subject's total number of reported wins, Y_i , gives us an unbiased estimator of subject i 's cheat rate:¹²

$$\hat{\theta}_i = \frac{1}{1 - p^*} \frac{1}{K} Y_i - \frac{p^*}{1 - p^*}$$

In our empirical analysis, we use this *estimated cheat rate*, $\hat{\theta}_i$, as our employed measure of subjects' propensity for dishonesty and regress this on subjects job preferences and various other characteristics. Relative to the true individual cheat rate, θ_i , our measure will suffer from measurement error due to the randomness in whether subjects actually win. Because $\hat{\theta}_i$ is an unbiased estimator of θ_i , however, replacing the true cheat rate with the estimated cheat rate as the outcome variable in a linear regression will still yield consistent and/or unbiased estimates under the usual assumptions.¹³

In relating our approach and estimates to methods used in the previous literature, three things are worth noting. First, since our estimated cheat rate $\hat{\theta}_i$ is just a linear transformation of the

¹²Unbiasedness is easily seen from $E(\hat{\theta}_i|\theta_i) = \frac{1}{1-p^*} \frac{1}{K} \sum_{k=1}^K P(y_{ik} = 1|\theta_i) - \frac{p^*}{1-p^*} = \theta_i$. It is worth noting that the estimated, $\hat{\theta}_i$, will be negative for any subject who reports winning fewer than $K \frac{p^*}{1-p^*}$ times, in spite of the fact that in fact $\theta_i \geq 0$ by assumption. It is possible to redefine the estimator and require that it is non-negative, however, the estimator would then no longer be unbiased.

¹³Because $\hat{\theta}_i$ is an unbiased estimator, the resulting measurement error, $(\theta_i - \hat{\theta}_i)$ is mean-independent of the true θ_i .

total number of reported wins, the common practice of using actual reported number of wins instead (or reported win rate) would only lead to a rescaling of the linear regression estimates presented later. Second, despite involving individual estimated cheat rates, our approach works even if $K = 1$. That is, even if each subject has only participated in a single round of the dice-under-cup game, a comparison of the estimated cheat rates among groups of subjects with different characteristics will allow us to estimate the true gap in average cheating rates between these groups (Houser, Vetter, and Winter 2012). We exploit this as a robustness check to evaluate differences in cheating behavior for a single dice game and the combined measure for all 40 rounds of the game. Third, an advantage of our statistical framework is that it is possible to examine the extent of measurement error in the estimates of individual dishonesty. In the appendix, we derive an expression for the extent of measurement error in the estimated cheat rate, $\hat{\theta}_i$ under the assumption that cheating behavior is independent across time. Measurement error is found to be decreasing in K and increasing in p^* . This motivates our chosen implementation of the dice-under-cup game, which has many rounds ($K = 40$) and a low win probability in each round ($p^* = \frac{1}{6}$).

3.3 Job sector preferences

The second key ingredient in the empirical analysis will be measures of subjects' preferences for public service jobs. For our main measure of job preferences, we asked respondents to imagine that they have obtained their academic degree and are now free to choose between jobs. In this scenario they were then asked to rank eight categories based on the most common jobs held by graduates from our student population: public administration, private sector job in the financial sector, private sector job in a political party or lobby organization, private sector job within public relations, private sector job in a law firm, a job in the Danish Central Bank, other public sector job, or other private sector job. As already noted, public administration is by far the most important public service career for our population. As our main measure of subjects' preferences for entering public service, we therefore use the rank given to public administration.

For robustness and additional results, we also elicited three additional measures of job preferences: First, respondents were asked the likelihood of them ending up in each of the eight

job categories described above. To ease subjects' way through the survey, we did not require that the reported probabilities sum up to a hundred so in the empirical analysis we rescale them appropriately. Second, we administered a standard 16-item questionnaire measuring Public Service Motivation (PSM), which in the political science literature is often used as an indication of respondents' dispositional preferences for working in the public sector (Perry 1996; Perry, Hondeghem, and Wise 2010).¹⁴

Finally, respondents were asked to compare their preferred job in the private versus public sector given various different counterfactual wage differences between the two jobs. For each of the different counterfactual wage scenarios subjects were asked to list which of the two jobs they preferred. A full translation of all dependent variables, including screenshots of how respondents were shown the items, are included in the appendix.

3.4 Other measures in the survey

In addition to the dice-under-cup game and the questions regarding job preferences, the survey experiment also included a few other standard experimental tasks and questions. To measure altruism and relative valuation of own income, we asked subjects to play a simple dictator game. At the beginning of the survey, subjects were given a gift of 15 DKK (2.5 USD). They were then offered to get the money transferred to their account when the survey was finished or donate some or all of the money to one of five charities of their choice. Furthermore, as they increased their own donation we matched their amount with up to 4 DKK (0.75 USD).

We also included an incentivized measure of risk aversion. Students were told that one in ten of them would be randomly selected to enter into a coin flip lottery at the end of the survey. They were then asked to choose between five different such lotteries with varying risk profiles. The most risky coin lottery involved a gain of 200 DKK (33 USD) in case of heads and 0 DKK for tails. The least risky lottery involved a gain of 80 DKK (16 USD) regardless of the coin flip.

As a proxy of ability, we asked subjects' to report their high school GPA. High school exams are standardized nationally in Denmark and provide a good measure of ability for our population of study. In the empirical analysis, we standardize GPAs across field to avoid mechanical

¹⁴Empirically, a number of studies have found PSM to correlate with employment in the public sector or preferences for employment in the public sector (Crewson 1997; Houston 2000; Lewis and Frank 2002).

correlations stemming from the admissions cut-offs for the different fields.¹⁵

To get measures of what is driving subject’ job preferences, we also asked them to rank the following five job characteristics in order of importance: salary, work hours and other terms of work, importance, entertainment value and job security.

Finally, we use data on the subjects’ gender. Table 1 provides summary statistics for all the main variables used in the empirical analysis. As the table shows, a few of the observations lack information about some variables. These are caused by erroneous reporting and a few subjects experiencing technical issues during parts of the survey experiment.¹⁶

Table 1: Summary statistics, key variables

Statistic	N	Mean	St. Dev.	Min	Max
Number of correct guesses	862	20.724	13.186	0	40
Estimated Cheat Rate	862	0.422	0.396	−0.200	1
Public administration ranked ≤ 2	862	0.422	0.494	0	1
Higher ranking of public administration	862	−3.414	2.079	−8	−1
Public service motivation score	860	2.440	0.521	0.250	3.950
Public sector picked at current wage	862	0.281	0.450	0	1
Probability of public administration	858	0.207	0.130	0	0.900
GPA (standardized)	861	−0.002	0.998	−5.914	2.332
Picks risky lottery	862	0.501	0.500	0	1
Job security ranked ≤ 2	862	0.119	0.325	0	1
Donation	862	6.798	6.521	0	15
Wage ranked ≤ 2	862	0.288	0.453	0	1
Male	862	0.536	0.499	0	1
Age	862	23.056	3.413	18	54
Field: Law	862	0.182	0.386	0	1
Field: Economics	862	0.442	0.497	0	1
Field: Political Science	862	0.376	0.485	0	1

The table shows summary statistics for the participants in the survey experiment. The variables are the number of reported correct guesses across the 40 dice games, the estimated cheat rate, an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual rank given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration, GPA standardized by field (the non-zero mean is due to the one excluded participant), an indicator for choosing the most risky lottery, the amount donated in the dictator game, the subject’s gender and age, indicators for whether job security and wage was ranked in the top two of the five job characteristics and indicator variables for field of study.

4 Empirical Analysis

Our empirical analysis of dishonesty and selection into public service in Denmark proceeds as follows. First, we examine how much heterogeneity in dishonesty exists among our student

¹⁵Admission to different fields in Danish higher education is based high school GPA, with the necessary GPA varying widely across different fields. This introduces strong mechanical differences in student GPAs across fields, which are unrelated to their own career preferences.

¹⁶Connectivity issues on subjects’ devices resulted in a few answers not being registered properly. In addition a few subjects reported all zeros when asked about the likelihood of ending up in the different jobs listed in the survey.

population and then whether there is evidence of self-selection of the more or less dishonest into public service. Next, we dig into what factors may be driving the pattern of selection. We do this in two steps by first examining which characteristics predict estimated cheating behavior and then examining which of these characteristics also correlate with wanting to enter public service. Finally, we present results regarding the effect of public sector wages on selection before discussing various robustness checks and additional results.

4.1 How much heterogeneity exists in dishonesty?

We are interested in examining whether Danish students who exhibit a preference for entering public service are noticeably more or less dishonest than other students, as measured by their cheating rate in our dice under-cup-game. For this to be the case, it is of course necessary that cheating does in fact occur among Danish students and that the rate of cheating also differs markedly across students. Figure 2 shows a histogram of the observed number of correct guesses across students in our experiment along with the distribution of correct guesses that would be expected under complete honesty. There are signs of extensive dishonesty. For example, the probability of an honest student having 10 or more correct guesses is about 12 percent, yet 73 percent of students report 10 or more correct guesses in our sample.¹⁷

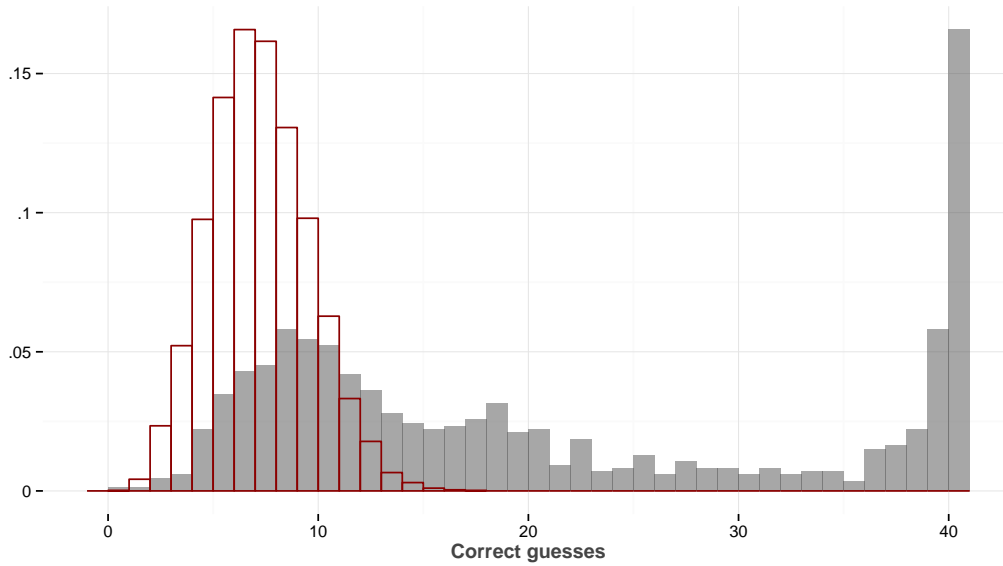
In terms of heterogeneity, the spread in the distribution of correct guesses also indicates that subjects differ in how much they cheat. As discussed in Section 3, however, the spread in the number of reported correct guesses confounds differences in the level of dishonest behavior with differences in luck during the dice-under-cup game. To accurately separate out the actual heterogeneity in dishonesty, we implement a maximum likelihood estimator for the distribution of cheating rates.¹⁸ Under the assumption that cheating behavior is independent over time, we estimate the full distribution of cheat rates using a flexible beta distribution mixture.¹⁹ Figure 3

¹⁷The focus of the present paper is only on the extent of heterogeneity in cheating in the sample and how this is related to job preferences; not the exact level of cheating. A brief comparison with the related results in Hanna and Wang (2013), however, suggests a somewhat higher level of dishonesty in our sample. For example, 54.8 percent of our subjects have winnings that are above the 99th percentile of the honest payoff distribution, as opposed to only 34.2 percent of the subjects in Hanna and Wang (2013). Besides the difference in setting and incentives, one obvious difference for the level of cheating is our computer-based implementation of the dice-under-cup game (see Jiang 2013).

¹⁸Econometric details of the estimator are given in the appendix.

¹⁹The results presented here are based on estimating the distribution of cheat rates as a mixture of two beta

Figure 2: Histogram of observed number of correct guesses and predicted distribution under full honesty (outlined).



The histogram shows the observed number of correct guesses in the data (filled) as well as the predicted distribution under full honesty.

shows the estimated distribution of cheat rates.

The estimated distribution show extensive heterogeneity in dishonesty among Danish students, including significant mass concentrated close to both zero and one. About 10 % are practically completely honest and cheat less than 1 % of the time, while 13 % are practically completely dishonest and cheat more than 99 % of the time.²⁰ The remaining 77 % fall somewhere in-between.²¹ Overall, the standard deviation of cheat rates across subjects is 0.39, relative to a mean of 0.42.

Given that the present paper is motivated in part by country-level differences in corruption, it is interesting to contrast these results with existing cross-country evidence on dishonesty. Using a version of the dice-under-cup game, Pascual-Ezama et al. (2015), find only very modest differences in the average cheating behavior across a sample of sixteen countries, including Denmark and India.²² With the obvious caveat that their implementation and subject pools

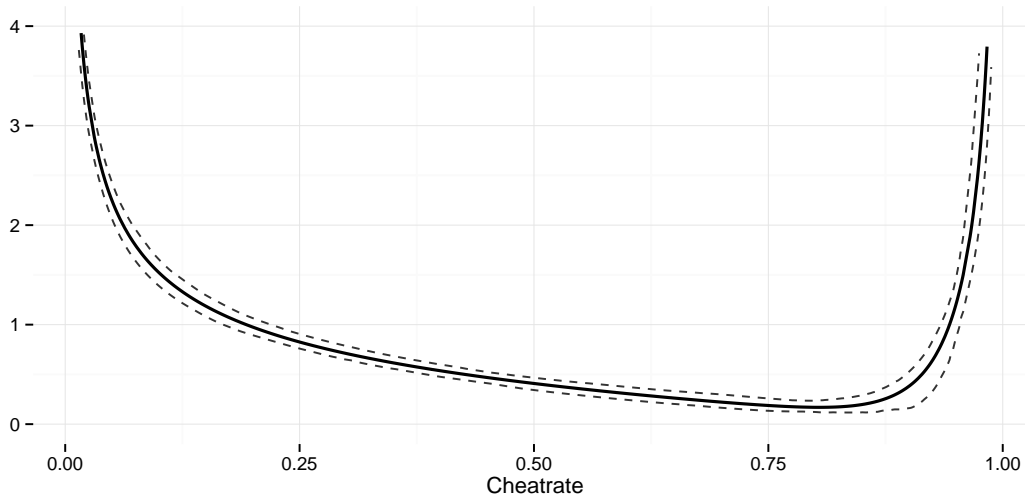
distributions. As shown in the appendix, this model fits the data very well. Based on standard model selection criteria and likelihood ratio tests, it is also preferred to richer models that include more beta distributions in the mixture or allow for mass points in the distribution.

²⁰Note that since we are modelling the cheat rate distribution as continuous, the share of people whose cheatrate is identically zero or one is zero by definition.

²¹The result that many subjects cheat a little bit but not the full amount is a standard finding in dice-under-cup games (Fischbacher and Föllmi-Heusi 2013; Hilbig and Hessler 2013; Shalvi, Handgraaf, and De Dreu 2011).

²²Across the full sample in Pascual-Ezama et al. (2015), Danish subjects report a win 51 % of the time compared to 54 % for Indian subjects.

Figure 3: Estimated distribution of cheat rates



The figure plots the probability density function of the distribution of cheat rates across students, estimated by maximum likelihood by fitting a beta distribution mixture with two components. The estimated mixture weights and distribution parameters are shown in the appendix. Dotted lines show pointwise 95% confidence intervals obtained via bootstrapping. Note that the y-axis is truncated; the function goes to infinity at the endpoints.

differ from ours, this is at least suggestive that within-country differences in dishonesty are more pronounced than differences across countries.

4.2 Do more or less dishonest students self-select into public service?

Having documented that Danish students differ markedly in dishonesty, we next examine if dishonesty is systematically related to preferences for entering public service. In Table 2, we regress subjects' estimated cheat rates on preferences a public service career. Column 1 focuses on our main measure of job preferences: whether subjects' rank public administration in the top two of the eight job categories described in Section 3. Students ranking public administration in the top 2 cheat about 10 percentage point less than other subjects and this difference is highly statistically significant. In Denmark, *less* dishonest subjects express a stronger preference for entering public service.

For transparency and robustness, the rest of the columns in the table presents corresponding results using alternative measures of public sector job preferences from our survey. In column 2 we replace the indicator variable from column 1 with the flipped actual rank given to public administration (so a higher value means a stronger preference for public service). In column 3 we

Table 2: Main results

	Estimated Cheat Rate				
	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.102*** (0.027)				
Higher ranking of public administration		-0.022*** (0.006)			
Public service motivation score			-0.152*** (0.025)		
Public sector picked at current wage				-0.090*** (0.030)	
Probability of public administration					-0.285*** (0.103)
Constant	0.465*** (0.018)	0.345*** (0.026)	0.793*** (0.063)	0.447*** (0.016)	0.481*** (0.025)
N	862	862	860	862	858
R ²	0.016	0.014	0.040	0.010	0.009

The table shows regressions of subjects' estimated cheat rate on various measures of public service job preferences. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual rank given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

use the measured PSM score. In column 4 we use data from our counterfactual wage question, focusing on whether subjects would choose the public sector over the private sector if faced with a sectoral wage gap of 5,000 DKK (833 USD), corresponding to the typical gap in starting wages between the two sectors. Across all these measures we see a negative and highly significant correlation between cheat rates and expressing a preference for entering public service.

The aim of this section is to examine the unconditional pattern of selection in our student population. Since we sample students conditional on having already chosen to enter one of the three fields, law, economics and political science, however, it is of particular interest to see whether our results are purely driven by selection into the different fields prior to our sampling. In Table 3 we therefore examine selection conditional on field of study by including field controls in the regressions from Table 2. We see that the estimated coefficients across the different measures of job preferences drop by between a half and two-thirds when field controls are included but remain sizable and at least marginally significant for two of the five measures. Selection into different fields thus seems to be part of the overall result but the pattern also appears present within fields. From the field controls, we also see that students of economics are significantly more likely to cheat than other students. This echoes previous results regarding economics as a field (e.g. B. Frank and Schulze 2000).

Table 3: Main results with control for subjects' field of study.

	Estimated Cheat Rate				
	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.045* (0.027)				
Higher ranking of public administration		-0.009 (0.006)			
Public service motivation score			-0.089*** (0.026)		
Public sector picked at current wage				-0.030 (0.029)	
Probability of public administration					-0.055 (0.104)
Field: Economics	0.252*** (0.035)	0.254*** (0.035)	0.249*** (0.035)	0.252*** (0.036)	0.255*** (0.035)
Field: Political Science	0.0003 (0.037)	0.0001 (0.037)	0.020 (0.037)	-0.007 (0.037)	-0.006 (0.037)
Constant	0.329*** (0.031)	0.279*** (0.039)	0.521*** (0.068)	0.321*** (0.031)	0.323*** (0.035)
N	862	862	860	862	858
R ²	0.112	0.111	0.121	0.110	0.109

The table shows regressions of subjects' estimated cheat rate on various measures of public service job preferences and indicator variables for field of study. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual rank given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

4.3 How is selection related to other student characteristics?

Having established that honest students are systematically more likely to want to enter public service in Denmark, we next try to shed some light on what underpins this pattern. In particular, we examine to what extent the pattern may be driven by students' with certain characteristics being both more dishonest and less likely to want to enter public service. In doing so we focus on four subject characteristics, which ex ante appear like plausible mediators of the relationship between dishonesty and job preferences:

Risk aversion has been shown previously to predict job choices (e.g. Buurman et al. 2012; Fouarge, Kriechel, and Dohmen 2014), as public jobs are often viewed as having higher job security. Moreover, a subject's risk tolerance could also correlate with their tolerance for dishonest behavior.

Ability has received significant attention in the literature on selection into public service (e.g. Dal Bó, Finan, and Rossi 2013; Ashraf et al. 2014; Deserranno 2014), and could also correlate with dishonesty.

Altruism, understood as subjects' willingness to forego own income to benefit others, is often found to predict job preferences (e.g. Dur and Zoutenbier 2014; Buurman et al. 2012; Kolstad

and Lindkvist 2012). In particular, since public service jobs in Denmark generally pay less than private sector jobs, altruistic subjects may be more willing to enter public service. As dishonesty generally involves personal gain at the expense of others, altruism could also be systematically related to dishonesty.

Finally, *gender* has been shown previously to be related to both job choices and dishonesty, as women are typically more likely to work in the public sector (Dur and Zoutenbier 2014; Buurman et al. 2012; Lewis and Frank 2002) and less likely to engage in dishonest behavior (Houser, Vetter, and Winter 2012; Bucciol, Landini, and Piovesan 2013).

We first examine how each of these characteristics relate to dishonest behavior. In Table 4, we regress the estimated cheat rate on measures of subjects' ability, risk aversion, altruism and gender.

Table 4: Estimated Cheat Rate and characteristics

	Estimated Cheat Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GPA (standardized)	0.007 (0.014)						0.014 (0.013)
Picks risky lottery		0.035 (0.027)					0.036 (0.027)
Job security ranked ≤ 2			0.002 (0.042)				-0.002 (0.040)
Donation				-0.016*** (0.002)			-0.016*** (0.002)
Wage ranked ≤ 2					0.083*** (0.030)		0.048* (0.029)
Male						0.061** (0.027)	0.034 (0.027)
Constant	0.422*** (0.013)	0.404*** (0.019)	0.422*** (0.014)	0.533*** (0.019)	0.398*** (0.016)	0.389*** (0.020)	0.481*** (0.028)
N	861	862	862	862	862	862	861
R ²	0.0003	0.002	0.00000	0.073	0.009	0.006	0.082

The table shows regressions of subjects' estimated cheat rate on various characteristics. The characteristics are GPA standardized by field, an indicator for choosing the most risky lottery, the amount donated in the dictator game, an indicator for being male and indicators for whether job security and wage was ranked in the top two of the five job characteristics. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

In column 1, subjects' GPA is effectively uncorrelated with their cheat rate, suggesting that dishonesty is unrelated to ability. In column 2, we fail to detect any correlation between the estimated cheat rate and whether the subject choose the most risky lottery in the lottery section of our survey. This suggests that risk preferences are uncorrelated with dishonesty, which is further borne out in column 3 where we see no relationship between cheat rates and whether or not a subject ranked job security among the two most important job characteristics, as described in Section 3.

In column 4 we see that donations in our dictator game is a clear negative predictor of dishonesty. Each additional 1 DKK donation is associated with a 1.6 percent lower cheat rate. One interpretation of this is that subjects who are less altruistic and place a higher weight on their own income are more likely to behave dishonestly, as this is a way to increase their own income. In line with this interpretation, column 5 shows that subjects who rate salary as an important job characteristic also cheat 8 percentage points more.

In column 6, male subjects are seen to behave more dishonestly, cheating about 6 percent more than their female counterparts.

Finally, in column 7 we simultaneously include all the various regressors. This specification confirms donation in the dictator game and the ranking of salary as a job characteristic as clear predictors of dishonesty, whereas gender is insignificant and has a smaller estimated coefficient. As our different measures of subject characteristics are correlated with each other and may suffer from different degrees of measurement error, care is warranted when interpreting regressions that include many of them simultaneously. With that caveat in mind, however, the results are at least indicative that the observed gender differences in dishonesty may be related to gender differences in altruism and relative valuation of own earnings.

Having examined which subject characteristics correlate with dishonesty, we next examine which ones also correlate with preferences for entering public service. In Table 5, we regress a dummy for having ranked public administration as one of the top two preferred jobs on the same set of subject characteristics as in Table 4.

In column 1 we see that our proxy of ability, standardized GPA, is uncorrelated with job preferences. Ability appears uncorrelated with preferences for entering public service in our context. In column 2, we see some evidence that subjects who pick the most risky lottery in our survey are less likely to have a preference for a job in public administration ($p = 0.10$). On the other hand, column 3 shows that ranking job security as an important job characteristic is actually negatively correlated with expressing a preference for entering public service, although this is not statistically significant.

In columns 4 and 5, we see that both our measures of altruism and relative valuation of own income are strong predictors of job preferences. Column 4 shows that for each additional 1 DKK

Table 5: Preference for public employment and characteristics

	Public administration ranked ≤ 2						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GPA (standardized)	0.001 (0.017)						-0.002 (0.017)
Picks risky lottery		-0.058* (0.034)					-0.042 (0.034)
Job security ranked ≤ 2			-0.072 (0.052)				-0.093* (0.051)
Donation				0.009*** (0.003)			0.006** (0.003)
Wage ranked ≤ 2					-0.202*** (0.037)		-0.184*** (0.037)
Male						-0.126*** (0.033)	-0.092*** (0.034)
Constant	0.423*** (0.017)	0.451*** (0.024)	0.431*** (0.018)	0.364*** (0.024)	0.480*** (0.020)	0.490*** (0.025)	0.513*** (0.035)
N	861	862	862	862	862	862	861
R ²	0.00000	0.003	0.002	0.013	0.034	0.016	0.058

The table shows regressions of an indicator for subjects ranking public administration in the top two of the eight job categories on various characteristics. The characteristics are GPA standardized by field, an indicator for choosing the most risky lottery, the amount donated in the dictator game, an indicator for being male and indicators for whether job security and wage was ranked in the top two of the five job characteristics. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

a subject donated in the dictator game, the subject is 0.9 percentage point more likely to express a particular preference for working in public administration. Column 5 shows that subjects who rank salary as an important job characteristic are about 20 percentage points less likely to express such a preference.

Column 6 echoes the standard finding that women are more likely to work in the public sector by showing that men are about 13 percentage points less likely to express a preference for a public sector job compared to women.

In column 7 we again include the full set of variables in the model. This leads to estimated coefficients that are very similar to the previous columns, although the mixed results regarding risk preferences are further underscored as the negative correlation between job preferences and preferences for job security is now marginally statistically significant, while the correlation between job preferences and lottery choice is not.²³

Together, the results in Tables 4 and 5 show no evidence that the systematic relationship between dishonesty and preferences for entering public service in Denmark is related to ability or risk preferences, as neither of these correlate with dishonesty. On the other hand, subjects who donate little in our dictator game and rank salary as an important job characteristic are

²³The very mixed empirical relationship between risk preferences and preferences for a job in public administration goes somewhat against the conventional view in the literature, that public sector jobs are more secure and therefore attract risk averse subjects. One possible interpretation is that for the highly educated group of subjects we consider here, the job security benefits in the public sector are negligible.

both systematically more dishonest and systematically less likely to want to enter public service. Altruism and relative valuation of own income thus appears to play a role in shaping the observed pattern of self-selection. The results also suggest a role for gender, as men are both more dishonest and less likely to want express a preference for entering public service. As noted, however, this in turn also appears to stem from gender differences in altruistic and valuation of own income.²⁴

4.4 How is the selection pattern related to public sector wages?

As in many countries, public sector jobs in Denmark generally pay less than private sector jobs. In light of the results in the previous section, one reason for the observed pattern of self-selection may be that dishonest students self-select out of the public sector and into higher-paying private sector jobs because they are less altruistic and place a higher relative weight on their own income.

To further examine this possibility, Table 6 splits the sample into an “honest” and a “dishonest” half based on the estimated cheat rate and then compares how many students in each group rank the eight different job category as their most preferred. The last row of the table thus essentially restates the paper’s main results by showing that public administration is ranked as the top job much more often for honest students than dishonest students: 25.9 % of the honest half of students rank public administration as their preferred job, while only 17.3 % of the dishonest half do so.

Looking at which jobs the dishonest half of students rank in the top instead of public administration, we see that the most important category is the financial sector. 18.9 % of dishonest students rank the financial sector at the top versus only 8.6 % among honest students. As financial sector jobs stand out as the highest paying of the listed job categories, this pattern supports the idea that pecuniary incentives play a role in making dishonest students self-select out of the public sector.

²⁴In the appendix we further regress the estimated cheat rate on the variable measuring preferences for entering public service while adding the various other characteristics as controls to see how this affects the estimated relationship between job preferences and dishonesty. Consistent with the discussion in the present section, the estimated relationship between job sector preferences and dishonesty is largely unaffected when controls for ability or risk preferences are added, however, the relationship weakens noticeably when donation behavior or ranking of salary is entered as control variables and to a lesser extent when gender is included. We note that the estimated correlation between job sector preferences and dishonesty remains highly significant throughout. With the caveat that our measures of altruism may suffer from measurement error, this suggests that factors beyond gender, altruism and valuation of own income are also important for the observed pattern of self-selection.

Table 6: Top ranked job categories among less and more dishonest

Top ranked job	Est. cheat rate < median	Est. cheat rate \geq median	Difference	p-value
Financial sector	8.62	18.94	10.31	0.0000
Central bank	4.66	10.16	5.50	0.003
Other private	19.11	20.79	1.67	0.60
Law firm	11.89	11.55	-0.34	0.96
Other public	3.96	3.23	-0.73	0.69
Public relations	6.76	4.16	-2.60	0.13
Lobby organization	19.11	13.86	-5.26	0.05
Public administration	25.87	17.32	-8.55	0.003

The table examines top ranked job categories among more dishonest vs. less dishonest subjects. Each row corresponds to a different job category. The first numerical column shows the fraction of subjects ranking each job category as the preferred one among subjects with an estimated cheat rate below the median. The second numerical column shows the fraction of subjects ranking each job category as the preferred one among subjects with an estimated cheat rate above the median. The last two columns shows the difference in these fractions for each of job category as well as the p-value for testing whether the difference is zero.

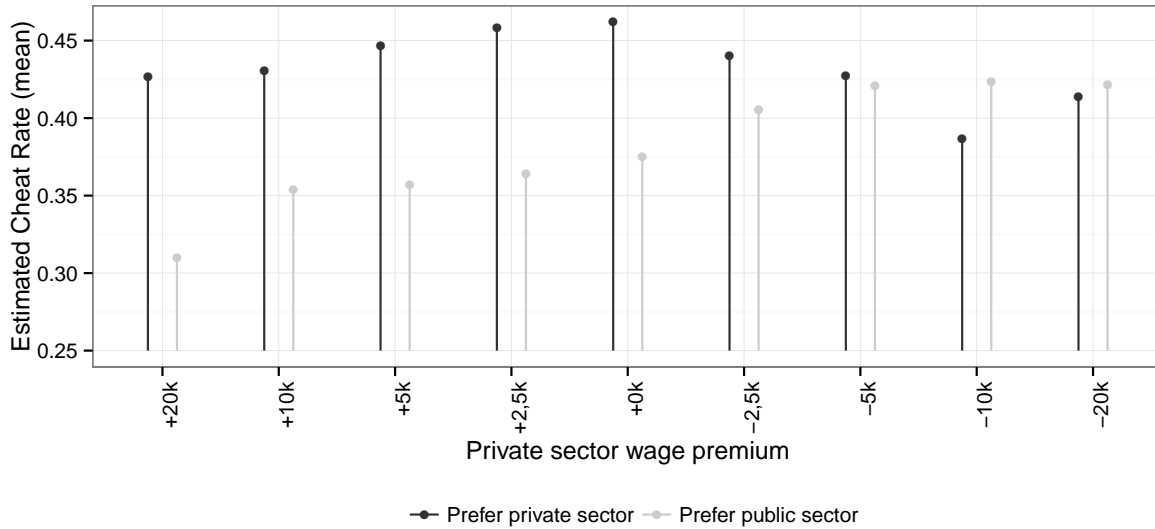
This apparent link between dishonesty and preference for higher wages has potential implications for one often discussed anti-corruption policy. Going back to at least Becker and Stigler (1974), increases in public sector wages have been viewed as a way to combat corruption. This builds on a standard efficiency wage argument that higher public sector wages raises the costs of being caught as corrupt and fired for individuals in public office. The results above, however, suggest that in Denmark, higher public sector wages might have a separate, countervailing effect on the selection into public office by making dishonest subjects with a high valuation of own income more interested in entering public service.

We can test this idea empirically using data from our set of counterfactual wage gap questions, where subjects were asked to choose between their preferred private and public sector jobs conditional on the two jobs having different possible wage gaps. Figure 4 shows the results.

Each pair of lines in the figure correspond to a different hypothetical wage gap between the public and private sector, ranging from the private sector paying 20,000 DKK more per month (3,333 USD) to the private sector paying 20,000 DKK less. For each wage gap, the height of the lines shows the average estimated cheat rate among those who would prefer the public and private sector, at the given wage gap. Furthest to the left, in the scenario where the private sector job pays 20,000 DKK more, the average estimated cheat rate among subjects preferring the private sector is 0.43 as opposed to only 0.31 among subjects preferring the public sector, a gap of 12 percentage points.

Moving right to scenarios where the public sector wage is relatively higher, the average cheat

Figure 4: Average cheat rate for those preferring public and private sector by size of public-private wage gap



The figure shows the averages estimated cheat rate among subjects preferring public and private sector in different counterfactual wage scenarios that vary the private sector wage premium. Each pair of one black and one grey line correspond to a different wage scenario. Black lines show the estimated cheat rates of those choosing the private sector in the wage scenario. Grey lines shows the estimated cheat rates for those choosing the public sector.

rates in the two groups change and move closer together.²⁵ In the scenario where the private sector pays 5,000 DKK, roughly the current level of the public-private wage gap in Denmark for our student population, the gap in cheat rates is down to 9 percentage points. Moving further right, the pattern continues. As the relative public sector wage is increased, the average cheat rate increases among public sector candidates and the public-private gap in dishonesty narrows and eventually flips in scenarios where the public sector wages is 10,000 DKK or more above the private sector wage. The answers in the counterfactual wage scenarios thus suggests that higher public sector wages would in fact lead to a more dishonest pool of candidates for public service jobs in Denmark.

4.5 Robustness and additional results

We finish this section of the paper by summarizing a few additional results and robustness checks that are presented at length in the appendix.

²⁵In the left-hand side of the figure, for scenarios where the private sector pays more, relative increases in public sector wages is seen to generally increase the average estimated cheat rate both for subjects choosing the private and public sector. This is due to the usual fact that shifting subjects between groups can increase the average in both groups if the shifted subjects lie below the average in their old group but above the average in their new group.

In the appendix, we examine a range of concerns with our implementation of the dice-under-cup game that we use to measure dishonesty. The fact that we ask subjects to play the same dice-under-cup game many times over, may raise concerns that subjects become fatigued or otherwise change their perception and behavior in the game over time. As noted in Section 3, however, it is possible to perform all of the regression analysis above using data from only a single dice roll for each subject. As a robustness check, the appendix includes a version of the analysis above using only data on the first dice roll for each subject. Besides the obvious loss of precision, this leads to virtually identical results.

Another concern would be if our results are only driven by subjects who cheat all of the time. Our sample includes 143 subjects who cheat on all dice rolls and report the maximum number of correct guess in our dice-under-cup games. As an additional sensitivity check, we repeated the empirical analysis without these subjects. As is shown in the appendix, our results hold also in this case.

Given the student population we focus on, a related concern is that some subjects in our sample may be explicitly aware of the academic literature on dishonesty and its relation to our experimental tasks. At the end of the survey experiment, we asked subjects whether they had prior familiarity with any of its elements. Independent coding of the responses show that 40 subjects expressed awareness of either dice-under-cup games, similar experimental games (e.g. coin flipping), or explicitly mentioned the potential for cheating. In the appendix we run our analysis after excluding these subjects. Doing so also does not affect the results.

Finally, as usual when analyzing survey or experimental data, representativeness and selective non-participation is a concern. In the appendix, we examine issues of non-participation by exploiting that the administrative university data contains information on enrollment year, field, completed classes and gender for everyone invited to our survey experiment. Although our participation rate of 28.8 % is reasonably high, our participant population does differ somewhat from invited non-participants. In particular, participants are a bit younger, more likely to study economics and slightly more likely to be male. Applying a reweighting procedure to correct our regression estimates for non-participation, however, shows no evidence that selective non-response has an impact on our results.

5 Conclusion

This paper is motivated by the possibility that differences in the selection of dishonest subjects into public service contribute to country-level differences in corruption. Previous evidence has shown that dishonest students are more likely to want to enter public service in highly-corrupt India. As a contrast, this paper examines selection into public service in the world's least corrupt country, Denmark.

We subject a relevant population of Danish students to a standard experimental dishonesty task and develop a novel method to estimate individual-level dishonesty from the experimental results. We document extensive heterogeneity in the propensity for dishonesty among Danish students and then relate this to job preferences and other student characteristics. In sharp contrast to previous findings in India, we find that dishonest students in Denmark are systematically *less* likely to want to enter public service. The very different patterns observed in the two countries suggest that differences in the dishonesty level of people who self-select into public service may play an important part in explaining differences in corruption across countries.

Examining further how the Danish selection pattern is related to student characteristics, we find no evidence that ability or risk-aversion plays a role. Conversely, we find that the observed selection pattern is driven in part by dishonest students self-selecting out of public service and into higher paid private sector jobs because they are less altruistic and place a higher weight on their own earnings opportunities. We also find that men are both more likely to be dishonest and less likely to work in the public sector, although this may in turn also reflect gender differences in altruism and valuation of own earnings.

Finally, we use counterfactual wage questions to examine whether relative changes in public sector wages would affect the pool of candidates willing to enter public service. In line with the finding that dishonest students are less altruistic and place more weight on own income, we find that higher public sector wages would attract *more* dishonest candidates to the public sector in Denmark.

Our findings suggest several new questions and avenues for further research. The hypothesis that dishonesty and selection into public service matters for country-level corruption builds on the premise that inherently dishonest individuals engage in more corrupt behavior. This

assumption appears plausible and finds support in the recent empirical studies of Hanna and Wang (2013) and Callen et al. (2015), however, a further examination of how subjects' inherent propensity for dishonesty shapes corrupt behavior in various contexts would clearly be very interesting.

Relative to India, the present paper documents a very different pattern of selection into public service in Denmark and sheds some light on what underpins the Danish selection pattern. The paper is silent, however, on *why* India and Denmark have such different patterns of selection. In a short companion paper, Barfort et al. (2015), we show theoretically that the observed patterns of selection may serve as self-sustaining equilibria. Even so, the question remains of why different countries end up in different equilibria. Examining which factors shape selection into public service along the dishonesty dimension thus appears like a fruitful topic for further research. As highlighted by our results regarding the effects of higher public sector wages, the effect of various policies on the selection of more or less dishonest individuals into public service should be a particular priority.

6 References

- Abbink, Klaus, and Danila Serra. 2012. "Anticorruption Policies: Lessons from the Lab." *Working Paper*, 77–115.
- Alatas, Vivi, Lisa Cameron, Ananish Chaudhuri, Nisvan Erkal, and Lata Gangadharan. 2009. "Subject Pool Effects in a Corruption Experiment: A Comparison of Indonesian Public Servants and Indonesian Students." *Experimental Economics* 12 (1): 113–32.
- Andvig, Jens Chr, and Karl Ove Moene. 1990. "How Corruption May Corrupt." *Journal of Economic Behavior & Organization* 13 (1): 63–76.
- Arbel, Yuval, Ronen Bar-El, Erez Siniver, and Yossef Tobol. 2014. "Roll a Die and Tell a Lie—What Affects Honesty?" *Journal of Economic Behavior & Organization* 107: 153–72.
- Ariely, Dan, Ximena Garcia-Rada, Lars Hornuf, and Heather Mann. 2014. *The (True) Legacy of Two Really Existing Economic Systems*. Munich Discussion Paper.
- Ashraf, Nava, Oriana Bandiera, Scott S Lee, and others. 2014. *Do-Gooders and Go-Getters: Career Incentives, Selection, and Performance in Public Service Delivery*. Suntory; Toyota International Centres for Economics; Related Disciplines, LSE.
- Banerjee, Ritwik, Tushi Baul, and Tanya Rosenblat. 2015. "On Self Selection of the Corrupt into the Public Sector." *Economics Letters* 127: 43–46.
- Barfort, Sebastian, Nikolaj A. Harmon, Asmus L. Olsen, and Frederik G. Hjorth. 2015. "A Formal Model of Corruption, Dishonesty and Selection into Public Service." *Working Paper*.
- Becker, Gary S, and George J Stigler. 1974. "Law Enforcement, Malfeasance, and Compensation of Enforcers." *The Journal of Legal Studies*, 1–18.
- Bernheim, B. Douglas, and Navin Kartik. 2014. "Candidates, Character, and Corruption." *American Economic Journal: Microeconomics* 5 (2): 205–46.
- Besley, Timothy. 2004. "Joseph Schumpeter Lecture: Paying Politicians: Theory and Evidence." *Journal of the European Economic Association*, 193–215.
- Buccioli, Alessandro, Fabio Landini, and Marco Piovesan. 2013. "Unethical Behavior in the Field: Demographic Characteristics and Beliefs of the Cheater." *Journal of Economic*

Behavior & Organization 93: 248–57.

- Buurman, Margaretha, Josse Delfgaauw, Robert Dur, and Seth Van den Bossche. 2012. “Public Sector Employees: Risk Averse and Altruistic?” *Journal of Economic Behavior & Organization* 83 (3): 279–91.
- Cadot, Olivier. 1987. “Corruption as a Gamble.” *Journal of Public Economics* 33 (2): 223–44.
- Callen, Michael, Saad Gulzar, Ali Hasanain, Yasir Khan, and Arman Rezaee. 2015. *Personalities and Public Sector Performance: Evidence from a Health Experiment in Pakistan*. National Bureau of Economic Research.
- Caselli, Francesco, and Massimo Morelli. 2004. “Bad Politicians.” *Journal of Public Economics* 88 (3): 759–82.
- Cohn, Alain, Ernst Fehr, and Michel André Maréchal. 2014. “Business Culture and Dishonesty in the Banking Industry.” *Nature* 516 (7529): 86–89.
- Cohn, Alain, Michel André Maréchal, and Thomas Noll. 2015. “Bad Boys: How Criminal Identity Salience Affects Rule Violation*.” *The Review of Economic Studies*.
- Crewson, Philip E. 1997. “Public-Service Motivation: Building Empirical Evidence of Incidence and Effect.” *Journal of Public Administration Research and Theory* 7 (4): 499–518.
- Dal Bó, Ernesto, Frederico Finan, and Martín A Rossi. 2013. “Strengthening State Capabilities: The Role of Financial Incentives in the Call to Public Service*.” *The Quarterly Journal of Economics* 128 (3): 1169–1218.
- Deserranno, Erika. 2014. *Financial Incentives as Signals: Experimental Evidence from the Recruitment of Health Workers*. Mimeo.
- Dohmen, Thomas, and Armin Falk. 2011. “Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender.” *The American Economic Review*, 556–90.
- Dollar, David, Raymond Fisman, and Roberta Gatti. 2001. “Are Women Really the ‘Fairer’ Sex? Corruption and Women in Government.” *Journal of Economic Behavior & Organization* 46 (4): 423–29.
- Dur, Robert, and Robin Zoutenbier. 2014. “Working for a Good Cause.” *Public Administration Review* 74 (2): 144–55.
- Fischbacher, Urs, and Franziska Föllmi-Heusi. 2013. “Lies in Disguise: An Experimental Study

- on Cheating.” *Journal of the European Economic Association* 11 (3): 525–47.
- Fisman, Raymond, and Edward Miguel. 2007. “Corruption, norms, and legal enforcement: Evidence from diplomatic parking tickets.” *Journal of Political Economy* 115 (6): 1020–48.
- Fisman, Raymond, Nikolaj A Harmon, Emir Kamenica, and Inger Munk. forthcoming. “Labor Supply of Politicians.” *Journal of the European Economic Association*.
- Fouarge, Didier, Ben Kriechel, and Thomas Dohmen. 2014. “Occupational Sorting of School Graduates: The Role of Economic Preferences.” *Journal of Economic Behavior & Organization* 106: 335–51.
- Frank, Björn, and Günther G Schulze. 2000. “Does Economics Make Citizens Corrupt?” *Journal of Economic Behavior & Organization* 43 (1): 101–13.
- Hanna, Rema, and Shing-Yi Wang. 2013. *Dishonesty and Selection into Public Service*. National Bureau of Economic Research.
- Hilbig, Benjamin E, and Corinna M Hessler. 2013. “What Lies Beneath: How the Distance Between Truth and Lie Drives Dishonesty.” *Journal of Experimental Social Psychology* 49 (2): 263–66.
- Hilbig, Benjamin E, and Ingo Zettler. 2015. “When the Cat’s Away, Some Mice Will Play: A Basic Trait Account of Dishonest Behavior.” *Journal of Research in Personality* 57: 72–88.
- Houser, Daniel, Stefan Vetter, and Joachim Winter. 2012. “Fairness and Cheating.” *European Economic Review* 56 (8): 1645–55.
- Houston, David J. 2000. “Public-Service Motivation: A Multivariate Test.” *Journal of Public Administration Research and Theory* 10 (4): 713–28.
- Jiang, Ting. 2013. “Cheating in Mind Games: The Subtlety of Rules Matters.” *Journal of Economic Behavior & Organization* 93: 328–36.
- Kaufmann, Daniel, Aart Kraay, and Massimo Mastruzzi. 2010. “The Worldwide Governance Indicators: A Summary of Methodology.” *Data and Analytical Issues, World Bank Policy Research Working Paper*, no. 5430.
- Kolstad, Julie Riise, and Ida Lindkvist. 2012. “Pro-Social Preferences and Self-Selection into

- the Public Health Sector: Evidence from an Economic Experiment.” *Health Policy and Planning*, czs063.
- Lewis, Gregory B, and Sue A Frank. 2002. “Who Wants to Work for the Government?” *Public Administration Review* 62 (4): 395–404.
- Lui, Francis T. 1986. “A Dynamic Model of Corruption Deterrence.” *Journal of Public Economics* 31 (2): 215–36.
- Olken, Benjamin A, and Rohini Pande. 2012. “Corruption in Developing Countries.” *Annu. Rev. Econ.* 4 (1): 479–509.
- Pascual-Ezama, David, Toke R Fosgaard, Juan Camilo Cardenas, Praveen Kujal, Robert Veszteg, Beatriz Gil-Gómez de Liaño, Brian Gunia, et al. 2015. “Context-Dependent Cheating: Experimental Evidence from 16 Countries.” *Journal of Economic Behavior & Organization*.
- Perry, James L. 1996. “Measuring Public Service Motivation: An Assessment of Construct Reliability and Validity.” *Journal of Public Administration Research and Theory* 6 (1): 5–22.
- Perry, James L, Annie Hondeghem, and Lois Recascino Wise. 2010. “Revisiting the Motivational Bases of Public Service: Twenty Years of Research and an Agenda for the Future.” *Public Administration Review* 70 (5): 681–90.
- Serra, Danila, Pieter Serneels, and Abigail Barr. 2011. “Intrinsic Motivations and the Non-Profit Health Sector: Evidence from Ethiopia.” *Personality and Individual Differences* 51 (3): 309–14.
- Shalvi, Shaul, Ori Eldar, and Yoella Bereby-Meyer. 2012. “Honesty Requires Time (and Lack of Justifications).” *Psychological Science* 23 (10): 1264–70.
- Shalvi, Shaul, Michel JJ Handgraaf, and Carsten KW De Dreu. 2011. “Ethical Manoeuvring: Why People Avoid Both Major and Minor Lies.” *British Journal of Management* 22 (s1): S16–27.
- Sønderskov, Kim Mannemar, and Peter Thisted Dinesen. 2014. “Danish Exceptionalism: Explaining the Unique Increase in Social Trust over the Past 30 Years.” *European Sociological Review*.

A Appendix

A.1 Additional econometric details for estimators

This section derives the variance of the individually estimated cheat rates used in the paper and goes through the construction of the maximum likelihood estimator for the full distribution of cheat rates.

In order to analyze the variance of the estimated cheat rate and construct estimators of the distribution of cheat rates, we will have to take a stance on the dependence of cheating behavior across rounds of the dice game. We focus here on the case where cheating behavior is independent across time. In this case, for an individual with cheat rate θ_i , the total number of reported wins, Y_i , is simply the number of successes in K independent trials with success probability $p^* + (1 - p^*)\theta_i$. Conditional on θ_i , Y_i therefore follows a binomial distribution:

$$Y_i|\theta_i \sim B(K, p^* + (1 - p^*)\theta_i) \quad (1)$$

Recall from the main text that our estimated cheat rate for each individual is $\hat{\theta}_i = \frac{1}{1-p^*} \frac{1}{K} Y_i - \frac{p^*}{1-p^*}$. Applying the standard formula for the variance of a binomially distributed random variable along with some simple algebra then yields the following expression for the variance of the estimated individual cheat rate:

$$Var(\hat{\theta}_i|\theta_i) = \frac{\theta_i(1 - \theta_i)}{K} + \frac{p^*}{(1 - p^*)} \frac{(1 - \theta_i)}{K}$$

From the above expression we see that the measurement error in our measure of dishonesty is increasing in p^* and decreasing in K . This motivates the design of our dice game which has a relatively low win probability, $p^* = \frac{1}{6}$ and asks students to repeat the dice game many times over, $K = 40$.

Next we turn to the construction of an estimator for the full distribution of dishonesty. From (1) it follows that conditional on θ_i the probability of observing some number of guesses Y_i is $\binom{K}{Y_i} (p^* + (1 - p^*)\theta_i)^{Y_i} (1 - p^* + (1 - p^*)\theta_i)^{K-Y_i}$. If we let F denote the distribution of θ_i

across the population, we can integrate out θ_i to get the unconditional probability of observing Y_i correct guesses:

$$\int_0^1 \binom{K}{Y_i} (p^* + (1 - p^*)\theta)^{Y_i} (1 - p^* + (1 - p^*)\theta)^{K - Y_i} dF(\theta)$$

The likelihood of observing a random sample of individuals with Y_1, Y_2, \dots, Y_N correct guesses is then:

$$\prod_{i=1}^N \int_0^1 \binom{K}{Y_i} (p^* + (1 - p^*)\theta)^{Y_i} (1 - p^* + (1 - p^*)\theta)^{K - Y_i} dF(\theta)$$

To estimate the distribution F using maximum likelihood, we will specify that F belongs to some parametric family parameterized by the vector $\lambda \in \Lambda$: $\mathcal{F} = \{F(\cdot; \lambda) | \lambda \in \Lambda\}$. With this specified, the problem of estimating the true F is equivalent to the problem of estimating the true λ . We can take logs above and construct an estimator of λ by maximizing the log likelihood function as follows:

$$\hat{\lambda} = \operatorname{argmax}_{\lambda} \sum_{i=1}^N \log \left(\int_0^1 \binom{K}{Y_i} (p^* + (1 - p^*)\theta)^{Y_i} (1 - p^* + (1 - p^*)\theta)^{K - Y_i} dF(\theta; \lambda) \right)$$

In the main text we implement this approach while setting \mathcal{F} to be the family of two-component beta mixture distributions so that λ consists of the mixture weights and the α - and β -parameters of the components. The next sections explore alternative models based on different families \mathcal{F} .

A.2 Estimated distribution of cheat rates, detailed results

This section presents additional results regarding the estimated distribution of cheat rates. Table 7 shows estimated parameters for three different models for the distribution. Model (1) is the one considered in the main text. It specifies the distribution of cheat rates as a mixture of two beta distributions with parameters and weights to be estimated. The table shows the estimated parameters and weights for each of the two components in the mixture, corresponding to the estimated cheat rate distribution plotted in the main text.

Model (2) in the table extends Model (1) by including an additional beta distribution in the mixture. The extra beta distribution is estimated to have a weight of about 0.05 and have very large α - and β -parameters. This corresponds to a beta distribution that is extremely concentrated around its mode of $\frac{\alpha-1}{\alpha+\beta-2} = 0.33$. In practice this estimated third estimated beta-distribution in the mixture is indistinguishable from a discrete distribution with all its mass at 0.33. This motivates Model (3) in the table which instead extends Model (1) by including a mass point in addition to the two-component beta-mixture. Similar to the results in Model (2), the included mass point is estimated to have a mass of about 0.05 and be located at 0.33.

Comparing the fit of the three models, the practical similarity of models (2) and (3) is evidenced by the fact that they both yield a log likelihood of -2835, whereas model (1) yields a slightly worse log likelihood of -2837. Since models (2) and (3) also include more free parameters, however, model selection based on standard information criteria (IC) suggests that Model (1) is preferred as it has a strictly smaller Bayesian IC than both Models (2) and (3) and a smaller or equal Akaike IC. Conducting Likelihood Ratio tests of Model (1) against Model (2) and Model (3), we also cannot reject Model (1) at any conventional level of significance ($p = 0.24$ and $p = 0.26$ respectively).¹

Finally, Figure 5 provides a different check on the fit of Model (1) by plotting the predicted distribution of correct guesses under the estimated distribution against the actually observed distribution of correct guesses. As the figure shows, the estimated distribution does a very good job of fitting the observed distribution.

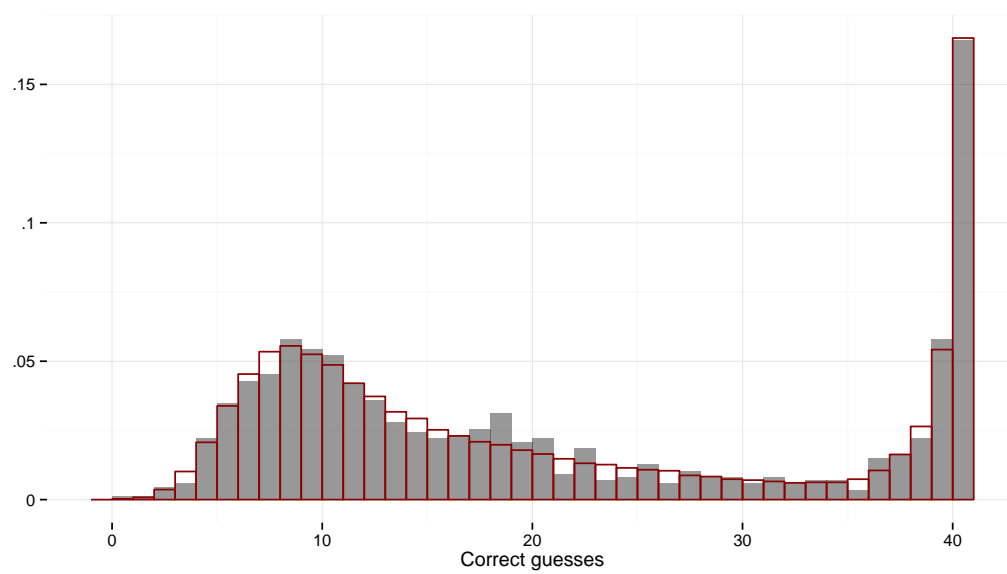
¹Testing Model (1) against the other models is non-standard in that it involves testing at the boundary of the parameter space. We therefore base the likelihood ratio test on McLachlan (1987)'s parametric bootstrap procedure for mixture distributions.

Table 7: Distribution of cheat rates, detailed estimates

	Model:		
	(1)	(2)	(3)
Beta-mixture component I:			
Weight	0.275 [0.242; 0.300]	0.273 [0.241; 0.310]	0.288 [0.249; 0.343]
α -parameter	18.9 [10.2; 47.2]	19.9 [7.7; 47.9]	19.7 5.71; 60.4]
β -parameter	0.485 [0.308; 1.02]	0.503 [0.292; 0.944]	0.503 [0.285; 0.992]
Beta-mixture component II:			
Weight	0.725 [0.700; 0.758]	0.675 [0.610; 0.728]	0.712 [0.656; 0.751]
α -parameter	0.510 [0.444; 0.583]	0.439 [0.341; 0.558]	0.438 [0.329; 0.581]
β -parameter	1.90 [1.51; 2.31]	1.73 [1.16; 2.56]	1.70 [1.12; 2.59]
Beta-mixture component III:			
Weight	-	0.0517 [0.0121; 0.103]	-
α -parameter	-	$4.13 \cdot 10^6$ [$3.12 \cdot 10^4$; $2.01 \cdot 10^7$]	-
β -parameter	-	$8.47 \cdot 10^6$ [$7.58 \cdot 10^4$; $3.68 \cdot 10^7$]	-
Additional mass point:			
Mass at point	-	-	0.0528 [0.0100; 0.103]
Mass point location	-	-	0.332 [0.243; 0.397]
Log likelihood	-2837	-2835	-2835
Akaike IC	5684	5687	5684
Bayesian IC	5708	5725	5718
p -value, LR-test H_0 : Model (1)	-	0.24	0.26

The table shows maximum likelihood estimates for the distribution of cheat rates based on three different model specifications. Model (1) specifies the distribution to be a two-component beta-mixture. Model (2) specifies the distribution to be a three-component beta-mixture. Model (3) specifies the distribution to be mixture between a two-component beta-mixture and a mass point. For each model the estimated parameters and mixture weights are shown along with resulting Log Likelihood, Akaike Information Criteria and Bayesian Information criteria. Bootstrapped 95% confidence intervals are in parenthesis. The last row shows the p -value of likelihood ratio tests of Model (1) vs. Model (2) and Model (3), respectively, based on the parametric bootstrap of McLachlan (1987).

Figure 5: Histogram of observed number of correct guesses and predicted distribution from main estimated cheat rate distribution



The histogram shows the observed number of correct guesses in the data (filled) as well as the predicted distribution based on the estimated distribution of cheat rates in Model (1) (outlined).

A.3 Factor analysis of dishonesty, job preferences and other characteristics

As an alternative to the sequential set of regressions in the main text, this section conducts a factor analysis of preferences for entering public service, dishonesty and the four additional student characteristics, ability, risk aversion, altruism and gender.

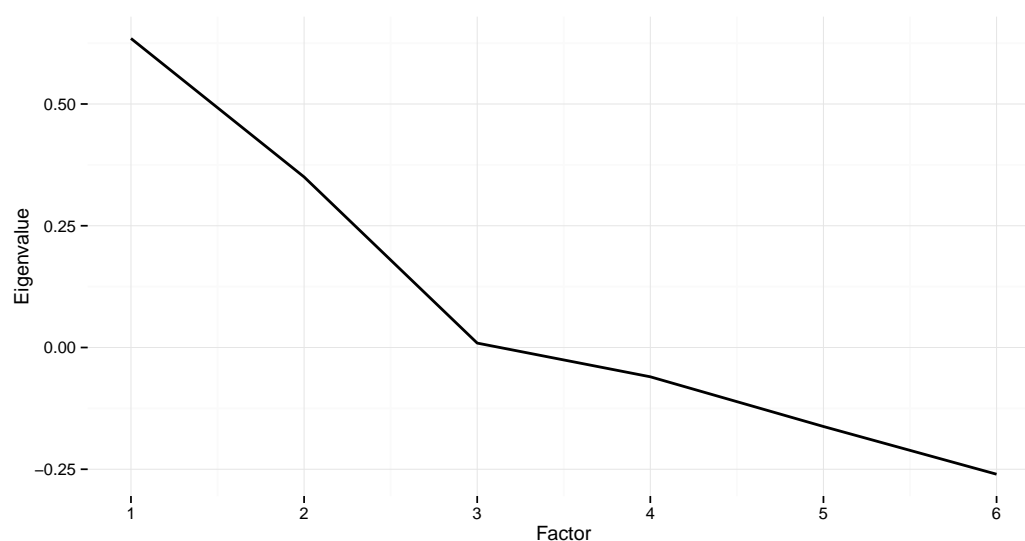
The variables used in the factor analysis are the flipped actual rank given to public administration (so that a higher value means a stronger preference), the estimated cheat rate, standardized GPA, the flipped riskiness rank of the chosen lottery (so that a higher value means more tolerance for risk), the amount donated in the dictator game and a dummy variable for being male. We compute the correlation matrix between these variables, using polychoric or polyserial correlations where appropriate to accommodate discrete variables² and apply the principal factor method.

To determine how many factor to retain, Figure 6 shows a Scree plot with the eigenvalues for the six identified factors. Looking at the line, the ‘elbow’ bends at the third component so we identify and proceed with two latent factors. We finally apply varimax rotation to the two factors to obtain interpretable loadings. Table 8 and Figure 7 show the resulting factor loadings.

Looking first at the factor loadings on the donation variable measuring altruism or relative valuation of own earnings, we see that it loads strongly on factor one but virtually does not load at all on factor two. Conversely the risk tolerance measure loads strongly on factor two but does not load on factor one. A useful interpretation of the factors is thus that factor one captures traits related to altruism or valuation of own earnings and factor two captures traits related to risk tolerance. With this interpretation in mind, the factor loadings tell a similar story to the analysis presented in the main text: Dishonesty, as measured by the estimated cheat rate, correlates negatively with altruism (factor one) but is unrelated to risk preferences (factor two). Preferences for entering public service shows a clear positive correlation with altruism and a less pronounced negative correlation with tolerance for risk. Altruistic individuals with a low relative valuation of own earnings are thus more dishonest and tend to self-selection out of public service. In terms of gender, men are significantly more tolerant of risk but also appear slightly

²Ignoring the discreteness of the variables and using the simple correlation matrix leads to virtually identical results.

Figure 6: Scree plot for factors



The figure shows a scree plot for the estimated factors. The x-axis corresponds to the six factors sorted by the size of the corresponding eigenvalue. The y-axis shows the eigenvalues for each factor.

less altruistic, implying that men are less likely to want to enter public service. Finally ability, as measured by GPA, is slightly negatively related to risk tolerance but essentially unrelated to altruism, implying that it is also unrelated to preferences for entering public service.

In sum, the conclusions of the paper's main text are robust to using factor analysis as an alternative method of analysis.

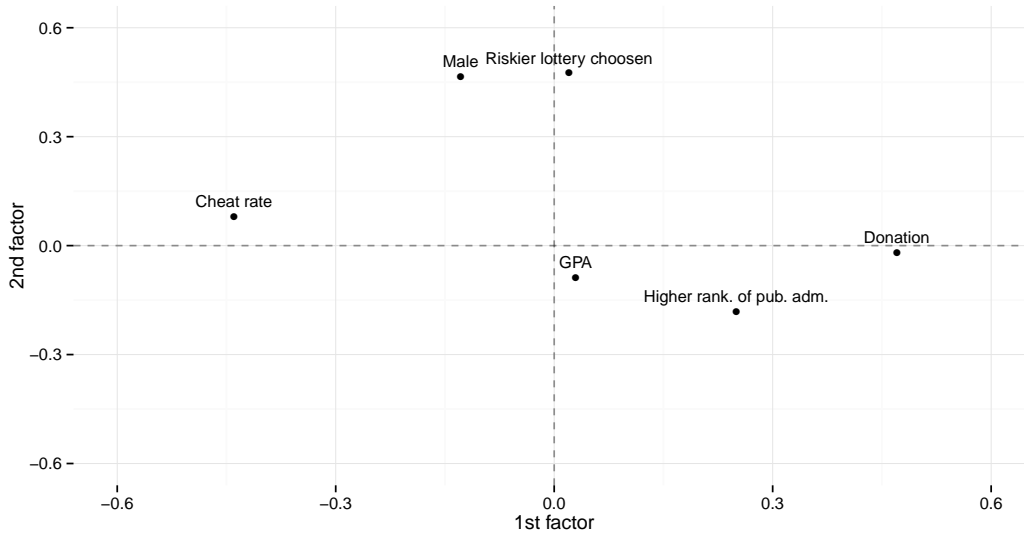
Table 8: Factor loadings after rotation

	Factor 1	Factor 2
Higher ranking of public administration	0.250*** (0.059)	-0.183* (0.107)
Estimated cheat rate	-0.440*** (0.046)	0.081 (0.063)
GPA (standardized)	0.029 (0.067)	-0.088 (0.080)
Riskier lottery choosen	0.021 (0.047)	0.475** (0.218)
Donation	0.471*** (0.043)	-0.018 (0.053)
Male	-0.128** (0.052)	0.465** (0.214)

The table shows the factor loadings of the two identified factors onto the six variables used in the analysis: the flipped actual ranked given to public administration (so that a higher value means a stronger preference), the estimated cheat rate, standardized GPA, the flipped riskyness rank of the choosen lottery (so that a higher value means more tolerance for risk), the amount donated in the dicator game and a dummy variable for being maleadministration. The results were obtained by principal-factor analysis on the a correlation matrix using polychoric and polyserial correlations as appropriate for the discrete variables, keeping the two most important factors and then applying the varimax rotation. Bootstrapped standard errors are in parenthesis.

*p < .1; **p < .05; ***p < .01

Figure 7: Factor loadings after rotation



The figure plots the factor loadings of the two identified factors onto the six variables used in the analysis: the flipped actual ranked given to public administration (so that a higher value means a stronger preference), the estimated cheat rate, standardized GPA, the flipped riskyness rank of the choosen lottery (so that a higher value means more tolerance for risk), the amount donated in the dicator game and a dummy variable for being maleadministration. The results were obtained by principal-factor analysis on the a correlation matrix using polychoric and polyserial correlations as appropriate for the discrete variables, keeping the two most important factors and then applying the varimax rotation.

A.4 Analyzing representativeness and selective nonparticipation

This section examines potential issues with selective nonparticipation among students invited for participation in our survey experiment. The concern is that students self-select into participation based on particular traits which creates selection bias in our estimates. In our experiment, 862 subjects ended up participating. Relative to the 3,000 e-mail invitations that was sent out, this yields a response rate of 28.8 percent.

One strength of our experimental design is that since we sample and invite students from the university registers, we have data also on the characteristics of those who do not participate. Table 9 compares participants to nonparticipants in terms of the available characteristics: field of study, age, gender and study experience as measured by the number of earned ECTS point (European Credit Transfer System). The table reveals some moderate systematic differences, with participants being on average younger and more likely to be male than the average nonparticipant. There are no mean differences between the two groups on study experience, although we find evidence of systematic differences in the distribution of the study experience variable.

Table 9: Comparing participants to invited non-participants

	mean participant	mean nonparticipant	diff	t test p value	KS p value
Age	24.128	25.176	-1.049	0.000	0.000
Female	0.466	0.503	-0.037	0.067	-
Study experience (ECTS points)	45.112	44.482	0.630	0.754	0.066
Field: Law	0.182	0.390	-0.207	0	-
Field: Economics	0.445	0.294	0.152	0	-
Field: Political Science	0.369	0.312	0.057	0.003	-

The table compares the sample of participants in the survey experiment with the sample of invited non-participants using the available data from university records. The available variables are student age, and indicator for the student being female, the students study experience as measured by the earned number of ECTS points (European Credit Transfer System), as well as indicators for field of study. Each row corresponds to a different variable. The first numerical columns shows the variable mean among participants, while the second column shows the mean among non-participants. The third and fourth columns show the difference in means between the groups and the p-value for a t-test that the means are the same. The last column shows the p-values for a Kolmogorov-Smirnoff test that the distributions of the variable is the same across the two groups.

To asses whether our results are driven by selective nonparticipation, we implement a correction based on inverse probability weighting. This method is intuitive and tractable, and the statistical properties of the inverse probability weighting method are well understood (Wooldridge 2002; Wooldridge 2007; Solon, Haider, and Wooldridge 2015). The validity of inverse probability weighting rests on the assumption that nonparticipation is random once we condition on all the observed data, a standard assumption when attempting to correct for systematic nonparticipation

(Gelman, King, and Liu 1999; King et al. 2001; Blackwell, Honaker, and King 2015; Solon, Haider, and Wooldridge 2015).

In practice, we model the participation probability by estimating a logit model on whether each subject participated in the experiment. We use the six variables in Table 9 as explanatory variables in the logit model. This generates, for each subject, a predicted probability of participating in the experiment. When the logit model is correctly specified, weighting each observation with the inverse of this probability generates consistent and unbiased regression estimates for the population (Wooldridge 2002). To obtain standard errors, we use a bootstrap procedure that resamples the full set of invitees.

Tables 10 through 13 show the full set results of the article when correcting for selective nonparticipation. The point estimates are generally close to those of the unweighted regressions, and there is little evidence that the results presented in the main text are dramatically changed by correcting for selective nonparticipation.

Table 10: Main result with reweighting to correct for non-participation

	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.084** (0.035)				
Higher ranking of public administration		-0.018** (0.008)			
Public service motivation score			-0.103** (0.043)		
Public sector picked at current wage				-0.069** (0.033)	
Probability of public administration					-0.173 (0.154)
Constant	0.418*** (0.027)	0.322*** (0.026)	0.633*** (0.115)	0.403*** (0.023)	0.419*** (0.044)

The table shows weighted regressions of subjects' estimated cheat rate on various measures of public service job preferences. The applied weights are the inverse of the predicted participation probability from a logit-model that includes age, an indicator variable for being male, study experience as measured by earned number of ECTS points and indicators for field of study. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual ranked given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Bootstrapped standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 11: Main result with field controls and reweighting to correct for non-participation

	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.054* (0.030)				
Higher ranking of public administration		-0.012 (0.008)			
Public service motivation score			-0.070* (0.040)		
Public sector picked at current wage				-0.030 (0.030)	
Probability of public administration					-0.051 (0.122)
Field: Economics	0.269*** (0.045)	0.271*** (0.043)	0.271*** (0.042)	0.267*** (0.045)	0.270*** (0.044)
Field: Political Science	0.005 (0.042)	0.006 (0.040)	0.020 (0.038)	-0.006 (0.042)	-0.005 (0.039)
Constant	0.320*** (0.045)	0.256*** (0.038)	0.462*** (0.115)	0.311*** (0.042)	0.312*** (0.052)

The table shows weighted regressions of subjects' estimated cheat rate on various measures of public service job preferences and indicator variables for field of study. The applied weights are the inverse of the predicted participation probability from a logit-model that includes age, an indicator variable for being male, study experience as measured by earned number of ECTS points and indicators for field of study. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual ranked given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Bootstrapped standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 12: Estimated cheat rate and characteristics with reweighting to correct for non-participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GPA (standardized)	0.035 (0.024)						0.041* (0.024)
Picks risky lottery		0.045 (0.036)					0.044 (0.030)
Job security ranked ≤ 2			0.007 (0.044)				0.013 (0.040)
Donation				-0.014*** (0.003)			-0.014*** (0.002)
Wage ranked ≤ 2					0.082** (0.036)		0.046 (0.032)
Male						0.077** (0.036)	0.046 (0.031)
Constant	0.390*** (0.015)	0.363*** (0.030)	0.384*** (0.020)	0.474*** (0.033)	0.361*** (0.023)	0.344*** (0.029)	0.423*** (0.037)

The table shows weighted regressions of subjects' estimated cheat rate on various characteristics. The applied weights are the inverse of the predicted participation probability from a logit-model that includes age, an indicator variable for being male, study experience as measured by earned number of ECTS points and indicators for field of study. The characteristics are GPA standardized by field, an indicator for choosing the most risky lottery, the amount donated in the dictator game, an indicator for being male and indicators for whether job security and wage was ranked in the top two of the five job characteristics. Bootstrapped standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 13: Preference for public employment and characteristics with reweighting to correct for non-participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GPA (standardized)	0.027 (0.025)						0.029 (0.028)
Picks risky lottery		-0.043 (0.046)					-0.036 (0.041)
Job security ranked ≤ 2			-0.007 (0.062)				-0.032 (0.058)
Donation				0.011*** (0.003)			0.009*** (0.003)
Wage ranked ≤ 2					-0.178*** (0.046)		-0.163*** (0.040)
Male						-0.117** (0.049)	-0.085* (0.044)
Constant	0.402*** (0.020)	0.419*** (0.036)	0.399*** (0.024)	0.330*** (0.031)	0.449*** (0.031)	0.459*** (0.036)	0.458*** (0.046)

The table shows weighted regressions of an indicator for subjects ranking public administration in the top two of the eight job categories on various characteristics. The applied weights are the inverse of the predicted participation probability from a logit-model that includes age, an indicator variable for being male, study experience as measured by earned number of ECTS points and indicators for field of study. The characteristics are GPA standardized by field, an indicator for choosing the most risky lottery, the amount donated in the dictator game, an indicator for being male and indicators for whether job security and wage was ranked in the top two of the five job characteristics. Bootstrapped standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

A.5 Additional robustness checks and results

Table 14: Horse race model

	Estimated Cheat Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Public administration ranked ≤ 2	-0.103*** (0.027)	-0.100*** (0.027)	-0.102*** (0.027)	-0.078*** (0.026)	-0.091*** (0.027)	-0.095*** (0.027)	-0.068** (0.027)
GPA (standardized)	0.007 (0.013)						0.014 (0.013)
Picks risky lottery		0.030 (0.027)					0.033 (0.027)
Job security ranked ≤ 2			-0.005 (0.041)				-0.008 (0.040)
Donation				-0.016*** (0.002)			-0.016*** (0.002)
Wage ranked ≤ 2					0.064** (0.030)		0.036 (0.029)
Male						0.048* (0.027)	0.027 (0.027)
Constant	0.466*** (0.018)	0.449*** (0.023)	0.465*** (0.018)	0.561*** (0.021)	0.441*** (0.021)	0.436*** (0.024)	0.516*** (0.031)
N	861	862	862	862	862	862	861
R ²	0.017	0.018	0.016	0.082	0.021	0.020	0.089

The table shows regressions of estimated cheat rate on a job preference measure with control various characteristics. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories. The characteristics are GPA standardized by field, an indicator for choosing the most risky lottery, the amount donated in the dictator game, an indicator for being male and indicators for whether job security and wage was ranked in the top two of the five job characteristics. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 15: Main results using only the first dice roll

	Estimated Cheat Rate (First Dice Roll)				
	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.097** (0.041)				
Higher ranking of public administration		-0.018* (0.010)			
Public service motivation score			-0.134*** (0.039)		
Public sector picked at current wage				-0.072 (0.045)	
Probability of public administration					-0.103 (0.156)
Constant	0.359*** (0.027)	0.256*** (0.039)	0.645*** (0.097)	0.338*** (0.024)	0.339*** (0.038)
N	862	862	860	862	858
R ²	0.007	0.004	0.014	0.003	0.001

The table shows regressions of subjects' estimated cheat rate on various measures of public service job preferences, where the cheat rate estimated is based only on the first dice game. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual rank given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 16: Main results excluding subjects with 100 pct win rate

	Estimated Cheat Rate				
	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.080*** (0.025)				
Higher ranking of public administration		-0.017*** (0.006)			
Public service motivation score			-0.093*** (0.024)		
Public sector picked at current wage				-0.053** (0.027)	
Probability of public administration					-0.209** (0.094)
Constant	0.342*** (0.016)	0.249*** (0.023)	0.537*** (0.061)	0.322*** (0.015)	0.351*** (0.023)
N	719	719	717	719	716
R ²	0.015	0.012	0.020	0.005	0.007

The table shows regressions of subjects' estimated cheat rate on various measures of public service job preferences, excluding subjects who reported a correct guess for all dice rolls. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual ranked given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 17: Main results excluding subjects with dice game experience

	Estimated Cheat Rate				
	(1)	(2)	(3)	(4)	(5)
Public administration ranked ≤ 2	-0.103*** (0.027)				
Higher ranking of public administration		-0.022*** (0.007)			
Public service motivation score			-0.144*** (0.026)		
Public sector picked at current wage				-0.093*** (0.030)	
Probability of public administration					-0.295*** (0.106)
Constant	0.453*** (0.018)	0.332*** (0.026)	0.762*** (0.064)	0.435*** (0.016)	0.470*** (0.026)
N	822	822	820	822	818
R ²	0.017	0.014	0.037	0.011	0.009

The table shows regressions of subjects' estimated cheat rate on various measures of public service job preferences, excluding subjects that explicitly indicated that they were cheating or had prior knowledge of the dice task. The exclusion is based on an independent coding of subjects responses in an open-ended text box in which subjects were asked about their impression of the survey and whether they had prior familiarity with any of its elements. The job preference measures are an indicator for whether public administration was ranked in the top two of the eight job categories, the flipped actual ranked given to public administration (so that a higher value means a stronger preference for public administration), the public service motivation score, an indicator for whether the public sector was picked in the wage scenario corresponding to the current wage gap, the subjective probability of ending up in public administration. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

A.6 Screenshots and instructions from survey experiment

Below we present translated instructions and screenshots from the survey experiment:

A.6.1 Dice games: Dishonesty measure

Translated instructions:

You have now responded to the first series of questions.

The purpose now is to see how you guess in situations marked by randomness. You will play 10 rounds of a dice game in which you can win money in each round.

You have to guess what the die will show. The more die rolls you guess, the more money you will win.

Each round of the game proceeds like this:

1. First, you will have to guess a number of dots from 1 to 6. When you have made your guess you can press the continue button.
2. Hereafter a die will roll and you will be asked to report the number of dots which you guessed earlier.
3. The next screen will show the result of the round. If your guess matched the number of dots on the die then you will win 3 DKK, else you will win 1 DKK.

You should avoid using the back button during the dice games as it might delete your total winnings.

Note: it is important that you are careful about remembering and reporting the exact number of dots which you guessed prior to rolling the die.

Figure 8: Intro screen to first set of dice games as viewed by the respondent

UNDERSØGELSE BLANDT STUDERENDE VED KØBENHAVNS UNIVERSITET

Du har nu svaret på den første serie af spørgsmål.

Formålet er nu at undersøge hvordan du gætter i situationer præget af tilfældighed. Du skal derfor spille 10 runder af et terningespil, hvor du i hver runde kan vinde pengebeløb.

Du skal gætte, hvad terningen slår. Jo mere rigtigt du gætter, desto større beløb vinder du.

Hver runde af terningespillet foregår således:


1. Først skal du gætte et antal øjne fra 1 til 6. Når du har lagt dig fast på et gæt, trykker du på fortsæt-knappen
2. Der vil herefter blive slået med en terning, og du vil blive bedt om at indtaste det antal øjne, du gættede på tidligere
3. Den næste skærm viser resultatet af runden. Hvis dit tal matcher terningens øjne, vinder du **3 kr.**, ellers vinder du **1 kr.**

Under terningsspillene skal du lade være at bruge din browsers "back"/"tilbage" knap da dette kan komme til at slette noget af din gevinst.

Bemærk: det er vigtigt, at du er grundig med at huske og angive netop det tal, du tænkte på før du slog med terningen.

Figure 9: Dice game test screen as viewed by the respondent

Før vi går i gang med terningspillet vil vi gerne høre om reglerne er klare. Vi vil derfor bede dig om at rapportere hvad en person vinder i denne situation


Screenshot

Terningslaget blev en 2'er.

Hvilket tal tænkte du på? Indtast i feltet:

Rapportér dit svar her

Vi vil også gerne bede dig rapportere hvad en person vinder i denne situation

Screenshot

Terningslaget blev en 1'er.

Hvilket tal tænkte du på? Indtast i feltet:

Rapportér dit svar og tryk derefter på fortsæt knappen for at gå i gang med terningspillene.

Figure 10: Intro screen: *Guess a number between 1 and 6. Hereafter, press the bottom below in order to throw with the digital die.*

UNDERSØGELSE BLANDT STUDERENDE VED KØBENHAVNS UNIVERSITET

Gæt på et tal mellem 1 og 6. Tryk derefter på knappen forneden for at slå med den digitale terning.

Slå!

Figure 11: Guess report screen (following a three second animation of spinning die): *The die throw was six. Which number did you guess? Please report in the field:*

UNDERSØGELSE BLANDT STUDERENDE VED KØBENHAVNS UNIVERSITET

Gæt på et tal mellem 1 og 6. Tryk derefter på knappen forneden for at slå med den digitale terning.



Terningetallet blev en 6'er.

Hvilket tal gættede du på? Indtast i feltet:

Submit

Figure 12: Payoff screen (in case of wrong guess): *Your guess did not match the die. You win 1 DKK. Your combined winnings in the survey amounts to 16 DKK.*

UNDERSØGELSE BLANDT STUDERENDE VED KØBENHAVNS UNIVERSITET

Dit gæt matchede ikke terningetallet. Du vinder 1 kr.

Din samlede gevinst for undersøgelsen hidtil er nu 16 kr.

Fortsæt

A.6.2 Donation: Altruism measure

Translated instructions:

Welcome to the study. Before we proceed, you are given a gift of 15 DKK (2.75 USD) as an appreciation of the time you spend on the survey. After the survey you will have the option to get this sum automatically transferred to your bank account together with the additional rewards you collect in the survey. But you can also choose to donate some of the money to one of the following charities:

- The Danish Cancer Society (Kræftens Bekæmpelse)
- DanChurchAid (Folkekirkens Nødhjælp)
- Save the Children (Red Barnet)
- Amnesty International
- Red Cross (Røde Kors)

Depending on how much you choose to donate we will additionally donate the amount provided in the below schema of donation options:

	Your donation	Our donation	Total donation
Option A	0 DKK	0 DKK	0 DKK
Option B	5 DKK	3 DKK	8 DKK
Option C	10 DKK	4 DKK	14 DKK
Option D	15 DKK	4 DKK	19 DKK

Which of the donation options do you choose?

- Option A
- Option B
- Option C
- Option D

Figure 13: Donation screen as viewed by the respondent. Following the screen participants who choose to donate an amount of money were asked which one of the five charities they wanted to donate to

UNDERSØGELSE BLANDT STUDERENDE VED KØBENHAVNS UNIVERSITET

Velkommen til undersøgelsen. Inden vi går videre modtager du allerede nu en gave på **15 kr.** som tak for at du tager dig tid til at deltage.

Efter undersøgelsen har du mulighed for at få udbetalt denne sum helt automatisk til din NemKonto sammen med de yderligere belønninger, du optjener i løbet af undersøgelsen. Men du kan også vælge at donere nogle af pengene til en af følgende velgørenhedsorganisationer:

- Kræftens Bekæmpelse
- Folkekirkens Nødhjælp
- Red Barnet
- Amnesty International
- Røde Kors

Afhængig af hvor meget du vælger at donere vil vi lægge en yderligere donation oveni som angivet i følgende skema over donationsmuligheder.

	Din donation	Vores donation	Samlet donation
Mulighed A	0 DKK	0 DKK	0 DKK
Mulighed B	5 DKK	3 DKK	8 DKK
Mulighed C	10 DKK	4 DKK	14 DKK
Mulighed D	15 DKK	4 DKK	19 DKK

Hvilken donationsmulighed vælger du?

☐ Mulighed A
☐ Mulighed B
☐ Mulighed C
☐ Mulighed D

Submit

A.6.3 Lottery: Risk aversion measure

Translated instructions:

The survey does, as already mentioned, among other things, deal with your decisions in situations marked by randomness. Among the participants in the study we draw a subset which participate in a simple coin-flip lottery. About one in ten participants will be selected to participate.

If you are selected to participate in the lottery a virtual coin will be flipped and you will win an amount of money depending on if the coin shows heads or tails. You can choose how the reward depends on the coin flip from the list of possible options below:

	Payoff if heads	Payoff if tails
Option A	200 DKK	0 DKK
Option B	160 DKK	30 DKK
Option C	140 DKK	40 DKK
Option D	120 DKK	50 DKK
Option E	80 DKK	80 DKK

Which of the donation options do you choose?

- Option A
- Option B
- Option C
- Option D
- Option E

Please press forward when you have made your choice. You will be informed about if you have been selected to participate in the lottery by the end of the survey.

Figure 14: Lottery screen as viewed by the respondent

UNDERSØGELSE BLANDT STUDERENDE VED KØBENHAVNS UNIVERSITET

Som sagt handler undersøgelsen bl.a. om dine beslutninger i situationer præget af tilfældighed. Blandt de deltagende i undersøgelsen trækker vi lod om muligheden for at deltage i et simpelt mønt-lotteri. Omkring hver tiende deltager vil få mulighed for at deltage.

Hvis du bliver trukket ud til at deltage i lotteriet vil der blive flippet en virtuel mønt og du vil vinde et antal kroner som afhænger af om mønten viser plat eller krone. Du skal selv vælge hvordan dine gevinster skal afhænge af mønten ud fra nedenstående liste af mulighed.

	Gevinst ved "krone"	Gevinst ved "plat"
Mulighed A	200 DKK	0 DKK
Mulighed B	160 DKK	30 DKK
Mulighed C	140 DKK	40 DKK
Mulighed D	120 DKK	50 DKK
Mulighed E	80 DKK	80 DKK

Hvilken mulighed vælger du?

- ☐ Mulighed A
- ☐ Mulighed B
- ☐ Mulighed C
- ☐ Mulighed D
- ☐ Mulighed E

Når du har valgt, bedes du trykke videre. Du vil først få at vide til sidst i undersøgelsen, om du er udvalgt til lotteriet.

Fortsæt

B Additional Appendix References

- Blackwell, Matthew, James Honaker, and Gary King. 2015. "A Unified Approach to Measurement Error and Missing Data: Overview and Applications." *Sociological Methods and Research*, 1–39.
- Gelman, Andrew, Gary King, and Chuanhai Liu. 1999. "Not Asked and Not Answered: Multiple Imputation for Multiple Surveys." *Journal of the American Statistical Association* 93 (433): 846–857.
- King, Gary, James Honaker, Anne Joseph, and Kenneth Scheve. 2001. "Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation." *American Political Science Review* 95 (1): 496–9.
- McLachlan, G J. 1987. "On Bootstrapping the Likelihood Ratio Test Statistic for the Number of Components in a Normal Mixture." *Applied Statistics* 36 (3): 318.
- Solon, Gary, Steven J Haider, and Jeffrey M Wooldridge. 2015. "What Are We Weighting for?" *Journal of Human Resources* 50 (2): 301–16.
- Wooldridge, Jeffrey M. 2002. "Inverse Probability Weighted M-Estimators for Sample Selection, Attrition, and Stratification." *Portuguese Economic Journal* 1 (2): 117–39.
- . 2007. "Inverse Probability Weighted Estimation for General Missing Data Problems." *Journal of Econometrics* 141 (2): 1281–1301.