CONTEMPORARY ECONOMIC POLICY

ON THE DETERMINANTS OF EDUCATIONAL CORRUPTION: THE CASE OF UKRAINE

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This article utilizes a unique data set to examine the relationship between a group of potential explanatory variables and educational corruption in Ukraine. Our corruption controls include bribing on exams, on term papers, for credit, and for university admission. We use a robust nonparametric approach in order to estimate the probability of bribing across the four different categories. This approach is shown to be robust to a variety of different types of endogeneity often encountered under commonly assumed parametric specifications. Our main findings indicate that corruption perceptions, past bribing behavior, and the perceived criminality of bribery are significant factors for all four categories of bribery. From a policy perspective, we argue that when bribe control enforcement is difficult, anti-corruption education programs targeting social perceptions of corruption could be appropriate. (*JEL* K42, J16, C14)

I. INTRODUCTION

Recent research has identified education as one of the sectors gravely infected by corruption. Educational corruption is by no means in its embryonic development; UNESCO[1] has classified it as a global problem. In fact, it represents a critical matter of interest to economists because it entails potentially harmful implications for labor market outcomes through reduced returns to education (Heyneman, Anderson, and Nuraliyeva 2007) and destruction of selection mechanisms created by educational institutions (Heyneman 2004); for the quality and accumulation of human capital (Osipian 2012); for the optimal allocation of talent (Fershtman, Murphy, and Weiss 1996); and for the quality of education whose impact is identified to reduce economic growth (Hanushek 2002; Hanushek and Kimko 2000), and inhibit economic development (Delgado, Henderson, and Parmeter 2013). While previous research has identified the effects of educational corruption on economic outcomes, our article seeks to fill a gap in the literature by exploring the relationship between educational corruption and a set of potential explanatory variables, using survey data from Ukraine.

Educational corruption is defined as: "the abuse of authority for personal as well as material gain" (Heyneman (2004)). Given the willingness of educators to exercise their authority in return for material gain (cash, gifts, etc.), students may participate in such mutually beneficial agreements if they believe better performance in education opens doors toward better job opportunities with higher compensation or social status. Students may also bribe to circumvent selection mechanisms or quality measures in place to distinguish themselves from their fellow students with the expectation of some other form of current or future gain. Such practices include, but are not limited to, bribing for university admission, high marks, or even paying for degrees. Educational corruption, however, is not limited to student-faculty exchange. The so-called "taxonomy" of educational corruption suggests that administrators and staff are also involved either through the embezzling of funds or by charging for services which are supposed to be offered for free (Rumyantseva 2005).

The purpose of this article is to investigate the relationship between educational corruption in Ukraine and a set of potential explanatory

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variables. Our contribution is threefold: First, we utilize a unique data set in order to examine both objective self-reported corruption involvement and subjective perceptions of corruption's existence, as opposed to only the subjective measures typically used. Second, we estimate the probability of students bribing on the following occasions: (1) exams (resit an exam), (2) credit (pass a test), (3) term papers, and (4) university admission. Third, due to the high probability of misreporting by survey respondents we address the possibility and implications of misclassification for the response variables, showing that the estimated coefficients identify the minimum impact of each of the covariates on *actual* bribing behavior. For estimation, we suggest a new nonparametric approach which places no restrictions on the error distribution and directly estimates the conditional density. We show that this approach is capable of capturing some common types of endogeneity likely to be present in our specific application.

To investigate our question of interest we use survey data from Ukraine. Despite the numerous anti-corruption projects implemented by the European Union and the United Nations Development Program, corruption in Ukraine is rampant in most sectors: e.g., police, courts, central authorities, mass media, MPs. Martsynkiv, Khutkyi and Reed (2006) report that Ukrainian citizens have a high level of both corruption perceptions and tolerance; nearly half are willing to bribe if needed, with one-fifth admitting to having paid a bribe in 2005. Osipian (2009) reports that nearly half of the citizens indicate that doing so is the most efficient way of solving problems. Most importantly, he documents the perception that the Ukrainian education sector, which includes kindergarten, primary schooling, and higher education institutions, is the most corrupt sector within the country.

As described by Osipian (2009), bribes in Ukrainian higher education institutions can be initiated by the student or the professor; in exchange for various forms of payment (often financed by the students' parents) students are granted the opportunity to improve their grade on an exam, resit exams, or gain entrance into institutions, circumventing standard practices. Despite its illegality, he argues that the mutually beneficial nature of the transaction leaves both participants sufficiently satisfied to execute the bribe. Ukrainian law enforcement agencies have made attempts to minimize the extent of educational corruption. As he points out, when the Ministry of Education and Science hosted a "hot line" where violations can be reported, students responded by calling in complaints regarding faculty's restraint in accepting bribes. This anecdote suggests that policies which increase the internalized costs of paying or receiving bribes may have a constraining effect on corruption.

While educational corruption is a widely discussed public issue in Ukraine, its determinants can be similar to other countries. Osipian (2009, 110) remarks that the Ukrainian education industry "might be no different from many other countries, and likely less than most former Soviet republics … " Across the four categories investigated, we find perceptions about the prevalence of corruption, attitudes toward the criminality of bribing, past bribing behavior, and gender to be significant explanatory variables for educational corruption. Our results suggest that a reasonable policy approach to combating corruption involves both reshaping peoples' perceptions and criminalizing bribing. Given the difficulty of anti-corruption law enforcement in countries with widespread corruption, our results offer policy makers support for a reasonable approach to combating educational corruption.

The article is organized as follows. Section II describes the data. The methodology is shown in Section III. Section IV presents our results. Section V concludes.

II. DATA DESCRIPTION

Most of the existing corruption literature presents evidence on the determinants of corruption at a cross country level.[2] As pointed out by Treisman (2000), "corruption is hard to study empirically" because many of its likely determinants may interrelate in complicated ways. Furthermore, corruption is hard to observe directly unless there is evidence stemming from surveys of corruption's victims. While he acknowledges that the accuracy of such surveys could be hard to assess, he does admit that the comparative evidence accumulating from surveys facilitated by a wide range of institutions during the last two decades is "surprisingly consistent."

Recent studies make extensive use of survey data to investigate corruption at the micro-level: Swamy, Knack, Lee, and Azfar (2001) and Svensson (2003), using data from Georgia

2. See Mauro (1995, 1996), Neeman, Paserman, and Simhon (2004), and Shaw, Katsaiti, and Jurgilas (2011) to mention a few.

and Uganda respectively, observe the extent to which firm owners were asked to solicit unofficial payments. In their study of Ukraine, Cabelkova and Hanousek (2004) rely on data on respondents' willingness to bribe in various hypothetical situations. Mocan (2008) uses data from 49 countries to measure individual-level corruption based on whether respondents had been asked or were expected to give a bribe to a government official.

As in Swamy et al. (2001), Svensson (2003), and Cabelkova and Hanousek (2004), we rely on country-specific data. The data were obtained from a 2002 survey conducted in Ukraine by *A Partnership for a Transparent Society*.[3] The survey was conducted in 12 cities across Ukraine and includes responses from a total of 1588 first- and second-year university students. The questions pertain to subjective perceptions of corruption in addition to objective frequencies of bribing on entrance, exams, term papers, and for credit in various tertiary education institutions. In addition, the survey includes information on students' beliefs about the criminality of bribing, past bribing behavior, gender, job prospects, city size, and parents' occupation.

What makes this data set unique is that it contains *self-reported bribing* in addition to perceptions of corruption, whereas existing corruption data sets offer information only on perceptions or willingness to bribe. Thus, the data allow us to expand methodologically and intuitively on the existing literature. In particular, it allows us to investigate (1) factors relevant for actual corruption as opposed to perceptions of corruption and (2) the relationship between actual bribing behavior and subjective corruption perceptions, as perceptions of corruption itself could be relevant for actual bribing behavior. Below we specify our particular measures of corruption and discuss a set of potential explanatory variables, linking them to the existing literature.

Our measures of corruption capture self-reported occurrences of students bribing (1) to enter their institutions, (2) on exams, (3) for credit, or (4) to pass a term paper. Among the descriptive statistics presented in Table 1, we report that 56% of the students gave an affirmative answer to the following question: "Did you give a bribe to enter the establishment?" Similarly, 22% of the students surveyed claimed to have bribed on an exam, 18% for credit, and 5% on a term paper. Given the nature of this questioning, misclassification is of major concern. This occurs if a student's bribing behavior differs from their reported behavior (i.e., a student actually bribed but reported that they did not). We address misclassification bias carefully in Section III.C.

Perceptions of corruption intensity within a student's own educational institution are categorized as follows: corrupt, when students report that they perceive their institution to be "very corrupt" or "rather corrupt"; and not corrupt, when students report "slightly corrupt," "not corrupt," or "hard to say." We acknowledge the fact that "hard to say" is a response with difficult interpretation and only draw inference on two categories of corruption perceptions. We hypothesize that perceptions of corruption itself will be a key explanatory variable for actual bribing behavior because, as argued in Cabelkova and Hanousek (2004), the willingness to bribe likely increases with the degree of corruption perceptions.

Students in the survey describe their perceptions regarding job market prospects. Four different possible answers on job prospects are considered: "the majority of students get a job," the student "expects to get a good job," "hard to say," and it will be "hard to get a job." A dummy variable is created taking the value 1 whenever the student answers "hard to get a job" and 0 otherwise. Respondents' job market perceptions are relevant as they may affect their decision on whether and when to bribe; students who perceive their job prospects to be poor may be more inclined to offer a bribe in order to differentiate themselves from their graduating cohort. One can argue that students rationally decide to bribe if the expected benefit (i.e., exam scores, final grades, admission to university) outweighs the cost. For a given cost, the expected benefit should increase the propensity to bribe. If education is perceived to perform a signaling mechanism in job search, the expected benefits of bribing are then higher.

Students are also asked to describe their sentiment toward bribing. In particular, if a student believes that a teacher accepting a bribe is a "criminal" or "a bribe-taker," then bribery is categorized as a crime. On the other hand, if a student feels that educators receiving bribes are "business people" or are "forced to" accept it, then bribing is classified as a noncriminal act. A third option is offered to the respondents who are "not sure." Variation in students' perception on whether bribing is a crime (Piliponyte 2002) affects their estimation of the expected cost of

3. This was a USAID-funded project and was carried out by Development Alternatives Inc.

TABLE 1
Descriptive Statistics

Variable	Description	Prop.	SD
Exam	1 if bribed on exam	.22	.010
Enter	1 if bribed to enter	.56	.012
Credit	1 if bribed for credit	.18	.010
Term	1 if bribed on term paper	.05	.006
Corrupt	1 if student perceives institution to be very or rather corrupt	.36	.012
Female	1 if student is female	.59	.012
Male	1 if student is male	.41	.012
Hard to Get Job	1 if student believes it will be hard to get a job	.36	.012
Under 17	1 if student is under 17 years of age	.06	.006
Between 17 and 19	1 if student is between 17 and 19 years of age	.74	.011
Over 19	1 if student is over 19 years of age	.20	.010
Big City	1 if population of city is >500,000	.51	.013
Large City	1 if population of city is <500,000 but >200,000	.24	.011
Medium City	1 if population of city is <200,000 but >100,000	.06	.006
Small City	1 if population of city is <100,000	.19	.010
Father in Private Sector	1 if father is in private of entrepreneurial sector	.30	.011
Father Is Cultural Worker	1 if father is a cultural worker	.28	.011
Father Not Working	1 if father is not working	.10	.007
Crime	1 if student views bribing as a crime	.48	.013
Not Crime	1 if student does not view bribing as a crime	.34	.012
Not Sure if Crime	1 if student is not sure bribing is a crime	.18	.010
Gold Medal	1 if student graduated with a gold medal from secondary school	.16	.009
Past Briber	1 if student bribed on final exams during secondary education	.27	.011
Not Working	1 if student does not currently work	.71	.011
Working	1 if student currently works	.29	.011

corrupt practices and hence their final decision on whether to conduct them.

Respondents also report employment status. University students typically depend financially on their parents. Thus, students who work can be assumed to have some extra pocket money to spend. Thus we include a dummy for student employment status in an attempt to capture an income effect on bribing (Mocan 2008). Moreover, as bribing could reduce the opportunity cost of working, there is further reason to hypothesize that students who work might be more likely to bribe. We also control for differences in gender and age as in Swamy et al. (2001) and Mocan (2008).

Father's employment status and occupation category are also relevant because family culture can be a source of corrupt behavior; a parent exhibiting corrupt behavior is more likely to raise a corrupt child. Following Cabelkova and Hanousek (2004) and Hauk and Sáez-Marti (2002) we control for father's employment and occupation as a proxy of family characteristics. Occupation categories are sliced into: entrepreneur/private sector employee; cultural worker; state employee; and in agriculture.

To account for city effects, we group the data by city size, following Cabelkova and Hanousek (2004). Cities are broken into four categories based on population size: "big cities" with population over 500,000; "large cities" with population between 200,000 and 500,000; "medium cities" with population between 100,000 and 200,000; and "small cities" with population of less than 100,000. Cabelkova and Hanousek (2004) hypothesize that, due to lack of social checks and balances, large cities might endorse more corrupt attitudes compared to small ones. The anonymity privilege that large cities offer could facilitate such behavior. Thus differences in social ethical structure based upon city size, as suggested by Hauk and Sáez-Marti (2002), can systematically be transmitted to students.

The survey also records information on whether a student received a gold medal[4] upon graduation from secondary education. This is used as a control for whether best performance

4. This is equivalent to graduating with honors from high school in the United States.

TABLE 2
Observed Difference in Bribing Frequencies across Explanatory Variables

	Exam	Enter	Credit	Term
Corrupt	.199***	.211***	.125***	.05***
Female	.048**	.045**	−.002	−.015*
Hard to Get Job	−.005	.006	−.032*	−.022**
Between 17 and 19	.021	−.017	.017	−.015
Over 19	−.04*	.01	−.034*	.018
Large City	−.054**	−.147***	−.053***	.02*
Medium City	.067*	.155***	−.102***	−.035*
Small City	.08***	.005	.071***	.057***
Crime	−.039**	−.04*	−.067***	.001
Past Briber	.085***	.199***	.047**	.053***
Not Working	−.036*	−.024	−.045**	.015

***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

at school is correlated with corrupt behavior in tertiary education. A word of caution at this point: This variable could have severe measurement bias because the gold medal could result either from hard work or from bribing. Thus the interpretation of the effect of this variable depends upon what it actually measures.

Finally, we investigate the relationship between bribing in secondary and bribing in tertiary education. If we hypothesize that bribing is a persistent behavior then bribing in high school should increase the probability of bribing at the university.

In Table 2 we report the observed difference in bribing frequencies across the four different types of bribes for each of the explanatory variables considered. The results suggest that perceptions of corruption in one's institution, attitudes toward the criminality of bribing, gender, and past behavior are potentially important. For example, women are 4.5% more likely to have bribed to enter an educational institution as compared to men. Similarly, those students who bribed on their final exams during secondary school are 20% more likely to have bribed to enter their educational institution as compared to those students who did not bribe during secondary school. Since these tests are not conditional on the complete information set, they are only suggestive. To estimate marginal effects using the complete information set, we next consider the estimation of conditional probabilities.

III. METHODOLOGY

A. *The Standard Approach*

In this section we introduce a set of possible parametric population models. Even though we *do not* rely solely on parametric methods to estimate our empirical model, the parametric structure we introduce here helps to describe the potential sources of endogeneity that could be present.

Our main objective is to estimate the probability of bribing across each of the four types of bribes we observe in the data set: bribing on exams, for entrance, for credit, and on term papers. Generally speaking, suppose we are interested in estimating the relationship between bribing (Y_1) and corruption perceptions (Y_2). Let $Y_1 = 1$ if a student bribed and zero otherwise and $Y_2 = 1$ if a student believes their educational institution is corrupt and zero otherwise. To demonstrate the sources of endogeneity that could be present in our model, we start with a parametric formulation where bribing and corruption perceptions are determined by a generalized simultaneous probit model:

(1)
$$Y_1^* = \gamma_{01} + Z_1\gamma_1 + \beta_{12}Y_2 + e_1, \quad Y_1 = 1\left[Y_1^* > 0\right]$$

(2)
$$Y_2^* = \gamma_{02} + Z_2\gamma_2 + \beta_{21}Y_1 + e_2, \quad Y_2 = 1\left[Y_2^* > 0\right]$$

where Z_1 and Z_2 are exogenous covariates. Under the above framework we can allow feedback between perceptions and bribing with feedback parameters β_{12} and β_{21}. Estimation of the probability of bribing for the above model is generally complex. However, if we are willing to assume that $\beta_{21} \times \beta_{12} = 0$ and that e_1 and e_2 evolve according to a bivariate standard normal distribution with a zero covariance ($\rho = 0$) then we can estimate a probit model where the probability of bribing is given by:

$$\text{(3)} \qquad \Pr\left(Y_1 = 1 | Y_2 = y_2, Z_1 = z_1\right) = G\left(\gamma_{01} + z_1\gamma_1 + \beta_{12}y_2\right)$$

where G is the standard normal cumulative distribution function. If on the other hand, $\rho \neq 0$ and we still have $\beta_{21} = 0$, then the appropriate model to estimate would be a bivariate probit as presented in Maddala (1983) and Wilde (2000). When one instead allows for $\beta_{21} \times \beta_{12} \neq 0$, estimation of the model is a bit more complex. For a detailed discussion of this case see Appendix A1. Based on the specification test performed on the standard probit model, we *reject* the null of a correctly specified model (see Appendix A2).

B. *A Nonparametric Approach*

To avoid a distributional and/or functional form specification error, we estimate the

conditional density directly using nonparametric methods.[5] This avoids placing restrictions on the distribution of the errors or the functional form of the underlying index function and allows for robust estimation. As shown by Racine, Li, and Zhu (2004) the nonparametric estimation of the conditional distribution dominates the typical probit approach when the model is misspecified. Their simulation evidence also shows that the nonparametric approach performs nearly as well as the probit, even when the model is correctly specified.

We can formulate our estimation framework as follows:

$$g\left(Y_1 = y_1 \mid \left[Y_2 \;\; Z_1\right] = x\right) = \frac{f\left(Y_1 = y_1, \left[Y_2 \;\; Z_1\right] = x\right)}{\mu\left(\left[Y_2 \;\; Z_1\right] = x\right)} \tag{4}$$

where Y_2 takes the value one if a student believes their institution to be corrupt and zero otherwise. Z_1 contains other control variables of interest such as past bribing behavior or gender. The function $g(Y_1 = y_1 | [Y_2 \; Z_1] = x)$ gives us the probability of observing a particular value of Y_1 conditional of some values for Y_2 and Z_1. In our example, Y_1 takes the value 1 if a student reported to have bribed and 0 otherwise. So the probability a student bribes, conditional on the explanatory variables taking some set of values, is given by the following expression:

$$\Pr\left(Y_1 = 1 | X = x\right) = \frac{f\left(Y_1 = 1, X = x\right)}{\mu\left(X = x\right)} \tag{5}$$

where $X = [Y_2 \; Z_1]$, $f(Y_1 = 1, X = x)$ is the joint distribution of Y_1 and X, and $\mu(X = x)$ is the marginal distribution for X. Normally researchers estimate this conditional probability by placing restrictions on the distribution of the errors given a fixed index function, as in the standard probit technique. We avoid making any distributional assumptions with this nonparametric approach, allowing for a flexible functional form. In fact, this approach captures a wide variety of specifications including a generalized multivariate probit.

We might also want to allow for the joint determination of different types of bribes. For example, bribing for entrance could increase the probability of bribing on an exam. To capture this in a parametric framework we would need to specify a joint distribution for the unobservables and also impose restrictions on the functional relationship between variables of interest. As shown in Appendix A3, the nonparametric model nests the univariate, bivariate, and simultaneous probit model without the need for such restrictive assumptions. This is an important result as it shows that the nonparametric approach can capture endogeneity due to either correlation in the unobservables or feedback between our variables of interest. These are two types of endogeneity likely to be present in our application. Moreover the nonparametric approach does not change methodologically regardless of the underlying population model. This differs substantially from the parametric approach where one has to derive the log-likelihood function for each population model under consideration.

A feasible estimator for Equation (5) can be obtained using the generalized product kernel function of Racine, Li, and Zhu (2004):

$$\hat{g}(y, x) = \frac{\sum_{i=1}^{n} K_{\gamma_1}\left(Y_{1i}, y\right) K_{\gamma_2}\left(X_i, x\right)}{\sum_{i=1}^{n} K_{\gamma_2}\left(X_i, x\right)} \tag{6}$$

where $K_{\gamma_2}(X, x)$ has the following representation:

$$K_{\gamma_2}(X, x) = W_h\left(X_i^c, x^c\right) L\left(X_i^d, x^d, \lambda\right) J\left(X_i^s, x^s, \lambda\right) \tag{7}$$

$$W_h\left(X_i^c, x^c\right) = \prod_{j}^{r_1} \frac{1}{h_j} w\left(\frac{X_i^c - x_j^c}{h_j}\right) \tag{8}$$

$$L\left(X_i^d, x^d, \lambda\right) = \prod_{j}^{r_2} \lambda_j^{I\left(x_j^d \neq X_i^d\right)} \left(1 - \lambda_j\right)^{1 - I\left(x_j^d \neq X_i^d\right)} \tag{9}$$

$$J\left(X_i^s, x^s, \lambda\right) = \prod_{j}^{r_3} \lambda_j^{\left|X_i^s - x_j^s\right|} \tag{10}$$

where X^c are continuous variables, X^d are discrete variables, and X^s are discrete variables with a natural ordering. The dimensions of X^c, X^d, and X^s are r_1, r_2, and r_3 respectively. γ_1 and γ_2 are the bandwidth parameters for the Y_1 and X variables.

We can recover the average marginal effect of corruption perceptions as follows:

$$\text{AME} = E\left[g\left(Y_1 = 1 | Y_2 = 1, Z_1\right) - g\left(Y_1 = 1 | Y_2 = 0, Z_1\right)\right]. \tag{11}$$

5. All code was written in MATLAB and is available upon request. We also direct the reader to the Hayfield and Racine (2008) nonparametric R code found at: http://www.economics.mcmaster.ca/faculty/racinej

An estimator for AME can be constructed as follows:

$$\widehat{\text{AME}} = \frac{1}{n}\sum_{i}^{n}\left[\widehat{g}\left(Y_1 = 1|Y_2 = 1, Z_{i1}\right) - \widehat{g}\left(Y_1 = 1|Y_2 = 0, Z_{i1}\right)\right]. \tag{12}$$

A similar expression can be obtained for any other variable of interest. This estimator can simply be thought of as a nonparametric average difference estimator. As shown by Coppejans and Sieg (2005), nonparametric average difference estimators are $\sqrt{n}$-consistent even when pointwise convergence takes on a much slower rate. Despite specification error, we also construct the average marginal effects for the probit model in a similar fashion for comparison and use the delta method in the construction of the 95% confidence intervals.

To calculate the optimal bandwidths we use the likelihood cross-validation method for which we minimize the following expression:

$$L = -\sum_{i=1}^{n}\ln\widehat{g}_{-i}\left(Y_{i1}|X_i\right) \tag{13}$$

where $\hat{g}_{-i}$ is the leave-one-out estimator of the conditional density. Notice that if this procedure produces a bandwidth for a zero–one variable for which λ_1=.5, this means that the variable is *irrelevant* in explaining the conditional value for Y_1. This immediately implies that its marginal effect is zero. This is a particularly appealing approach to selecting bandwidths via a data-driven method such as likelihood cross-validation. This method is capable of smoothing out irrelevant variables thus automatically reducing the dimension of X.

C. Misclassification

As noted earlier, the data may contain a significant amount of misclassification. Hausman, Abrevaya, and Scott-Morton (1998) derive a parametric and semiparametric approach to consistently estimate the marginal effects of a model in the presence of misclassification and show that the bias from misclassification can be large even with small classification probabilities. To see how misclassification impacts our results, it is instructive to think about misclassification probabilities:

$$\alpha_0 = \Pr\left(Y_{i1} = 1|\widetilde{Y}_{i1} = 0\right) \tag{14}$$

$$\alpha_1 = \Pr\left(Y_{i1} = 0|\widetilde{Y}_{i1} = 1\right) \tag{15}$$

where α_0 is the probability that a student did not bribe ($\widetilde{Y}_{i1} = 0$) but reports they did ($Y_{i1} = 1$) and α_1 represents the probability a student reports they did *not* bribe ($Y_{i1} = 0$) when they actually did ($\widetilde{Y}_{i1} = 1$). Given the nature of our data set, it is likely that of the two misclassification probabilities, α_1 is of the most concern. Students are more likely to misreport their behavior when they engaged in bribery as compared to when they did not. Assuming that the probabilities of misclassification are independent of the covariates, Hausman, Abrevaya, and Scott-Morton (1998) show that the probability of observing a $Y_i = 1$ conditional on a set of covariates is given by the following expression:

$$\Pr\left(Y_i = 1|X_i\right) = \alpha_0 + \left(1 - \alpha_0 - \alpha_1\right)F\left(h\left(X_i\right)\right) \tag{16}$$

where F is a nonspecified c.d.f. of the unobservables ($\varepsilon_i = Y_i^* - h\left(X_i\right)$) from an underlying latent variable (Y_i^*) and an unknown function $h(X_i)$. Under the assumptions that (1) $h(X_i) = X_i\beta$ and (2) F is the standard normal c.d.f., the parameters of the model ($\alpha_0, \alpha_1, \beta$), can be consistently estimated via maximum likelihood. If we assume $h(X_i) = X_i\beta$, but allow F to remain unspecified, we need a semi-parametric approach to estimate the marginal effects.

To see how misclassification can impact our estimated results, consider the case in which X takes only two values, 0 and 1. Estimating the marginal effect of this variable on Y_1 nonparametrically would produce an estimated value for $(1 - \alpha_0 - \alpha_1)(F(h(X = 1)) - F(h(X = 0)))$. If the misclassification probabilities are zero, then the marginal effects derived by Equation (11) represent the true marginal effect of X on actual bribing behavior ($\widetilde{Y}_1$). However, for non-zero values of α_0 and α_1, the marginal effects have to be scaled by $1/(1 - \alpha_0 - \alpha_1)$. In this case our reported marginal effects represent the lower bound, and in a sense, the minimum effect each variable could have on the probability of bribing. Hausman, Abrevaya, and Scott-Morton (1998) show that recovering the misclassification probabilities under a semi-parametric approach is not always possible or highly reliable so they suggest reporting the marginal effects over a range of values for α_0 and α_1. For example, suppose we ignore misclassification and estimate the marginal effect of corruption perceptions on the reported bribing for entrance to be .182. If we believe α_1=.4 and $\alpha_0 = 0$, then the marginal effect of corruption perceptions on *actual* bribing would be .182/(1-0-.4) = .303. Therefore, the

TABLE 3
Results for Exam Bribes: Average Marginal Effects

	Nonparametric Specification				Probit Specification		
			95% CI			95% CI	
Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	**L.B.**	**U.B.**	$\widehat{\text{AME}}$	**L.B.**	**U.B.**
Corrupt	.030	**.182**	.139	.221	**.202**	.147	.257
Female	.251	**.026**	.009	.045	**.053**	.003	.104
Hard to Get Job	.211	.007	−.018	.031	.008	−.037	.053
Between 17 and 19	.399	−.001	−.006	.003	−.045	−.114	.025
Over 19	.072	−.024	−.053	.008	−.080	−.151	−.009
Large City	.197	−.018	−.038	.003	−.035	−.084	.013
Medium City	.449	.001	−.001	.003	.070	−.024	.165
Small City	.000	**.108**	.055	.164	**.080**	.020	.140
Father in Private Sector	.300	−.007	−.021	.006	**−.048**	−.093	−.003
Father Is Cultural Worker	.488	.000	−.001	.001	−.024	−.071	.024
Father Not Working	.348	−.001	−.008	.006	−.018	−.086	.049
Crime	.242	**−.031**	−.048	−.009	**−.073**	−.115	−.031
Not Sure if Crime	.157	−.004	−.028	.019	−.030	−.084	.024
Gold Medal	.479	.001	.000	.002	.041	−.017	.099
Past Briber	.074	**.035**	.005	.070	**.050**	.002	.098
Not Working	.175	−.017	−.042	.012	−.034	−.085	.017

Results that are significant at the 5% level or greater are presented in bold.

impact of misclassification on the marginal effect of each X can be obtained for any combination of hypothesized values for α_0 and α_1.

IV. RESULTS

Table 3 reports the results for bribing on exams for the nonparametric and probit specifications. Given indication of specification error within the probit model, we believe the nonparametric estimates are more reliable. To enable direct comparison, we report both. Statistically significant coefficients are presented in bold.[6] Five controls appear to be significant with respect to bribing on exams. As intuitively expected and in agreement with the finding of Cabelkova and Hanousek (2004) on the positive effect of corruption perceptions on willingness to bribe, our results indicate that when students perceive their institution to be corrupt, they are more likely to bribe. Females, students attending institutions located in small cities, and students who have bribed in secondary education are found to have a higher probability to bribe for exams, whereas perceiving bribing as a crime is associated with a lower probability of bribing. While the probit model suggests that students with parents working in the private sector are less likely to bribe on an exam, this result is not verified by the robust nonparametric approach.

Our results on exam bribes above essentially act as a compass for the rest of the results on entrance, credit and term paper bribing, presented in Tables 4, 5, and 6 respectively. In all three cases, perceptions of widespread corruption inside the educational institution are associated with a higher probability of paying a bribe. Thus when students believe that their university is already corrupt, they are more likely to offer a bribe. In addition, we verify across all specifications that city size is negatively related to bribing behavior. Finally, we provide evidence that students' perceptions on the criminality of bribing are negatively associated with bribing. In agreement with the finding on exam bribes, our results indicate that females and students who exercised bribing in secondary education will also be more likely to pay bribes to be granted admission to higher education, while past bribing behavior is also associated with an increased likelihood to bribe on a term paper and for entrance.

In all four cases of bribing reported above (for exam, admission, credit and term paper) age, employment status of the student, gold medal in high school, and difficulty of getting a job appear not to significantly affect the probability of bribing.

6. The confidence intervals for the nonparametric AME are constructed using 300 bootstraps from the empirical distribution while the probit confidence intervals are constructed using a straight forward application of the delta method. Increasing the bootstraps has little to no effect on the confidence intervals constructed under the nonparametric specification.

TABLE 4
Results for Entrance Bribes: Average Marginal Effects

	Nonparametric Specification				Probit Specification		
			95% CI			95% CI	
Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	**L.B.**	**U.B.**	$\widehat{\text{AME}}$	**L.B.**	**U.B.**
Corrupt	.115	**.129**	.094	.163	**.191**	.143	.240
Female	.342	**.019**	.005	.033	**.060**	.012	.108
Hard to Get Job	.185	.013	−.019	.035	.019	−.030	.068
Between 17 and 19	.427	−.002	−.007	.004	−.038	−.140	.064
Over 19	.500	.000	.000	.000	−.037	−.148	.075
Large City	.000	**−.139**	−.197	−.090	**−.142**	−.200	−.084
Medium City	.000	.021	−.057	.103	.103	.003	.203
Small City	.335	−.004	−.014	.007	−.016	−.079	.048
Father in Private Sector	.500	.000	.000	.000	.009	−.051	.070
Father Is Cultural Worker	.500	.000	.000	.000	.005	−.055	.065
Father Not Working	.500	.000	.000	.000	.009	−.076	.093
Crime	.026	**−.067**	−.110	−.028	**−.086**	−.140	−.031
Not Sure if Crime	.201	−.021	−.039	.000	−.061	−.130	.008
Gold Medal	.000	−.040	−.091	.030	−.018	−.085	.048
Past Briber	.000	**.166**	.114	.219	**.163**	.110	.215
Not Working	.500	.000	.000	.000	−.020	−.072	.033

Results that are significant at the 5% level or greater are presented in bold.

TABLE 5
Results for Credit Bribes: Average Marginal Effects

	Nonparametric Specification				Probit Specification		
			95% CI			95% CI	
Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	**L.B.**	**U.B.**	$\widehat{\text{AME}}$	**L.B.**	**U.B.**
Corrupt	.031	**.127**	.088	.165	**.134**	.079	.188
Female	.500	.000	.000	.000	.005	−.047	.056
Hard to Get Job	.500	.000	.000	.000	−.029	−.071	.012
Between 17 and 19	.111	.010	−.020	.040	−.027	−.102	.047
Over 19	.500	.000	.000	.000	−.065	−.132	.003
Large City	.147	**−.032**	−.054	−.003	**−.052**	−.093	−.011
Medium City	.175	**−.025**	−.037	−.012	**−.102**	−.158	−.045
Small City	.343	**.013**	.004	.024	**.061**	.005	.117
Father in Private Sector	.390	−.003	−.010	.004	−.020	−.069	.028
Father Is Cultural Worker	.500	.000	.000	.000	−.004	−.053	.046
Father Not Working	.052	.015	−.021	.055	.015	−.054	.083
Crime	.085	**−.071**	−.104	−.041	**−.090**	−.133	−.048
Not Sure if Crime	.117	−.019	−.038	.009	−.058	−.102	−.013
Gold Medal	.424	−.001	−.005	.004	−.029	−.076	.019
Past Briber	.053	.029	−.009	.062	.023	−.023	.068
Not Working	.500	.000	.000	.000	−.039	−.096	.019

Results that are significant at the 5% level or greater are presented in bold.

In Figure 1 we illustrate how the misclassification probability (α_1) impacts the average marginal effect for corruption perceptions on each bribe type over the range $\alpha_1 \in [0,.5]$. As expected, if $\alpha_1 = 0$ the marginal effect of corruption perceptions corresponds to those listed in Tables 3–6; for $\alpha_1 \in (0,.5]$ the average marginal effect is strictly increasing. For example, when $\alpha_1 = 0$ the AME of corruption perceptions on the probability of bribing for entrance is .1290, as compared to .2580 when α_1=.50. Due to the simplicity of adjusting the marginal effects for different misclassification probabilities, further adjustments are left to the reader.

Tables 1–3 in the accompanying appendix present the results for the nonparametric estimation of the joint determination of bribes. Here we

TABLE 6

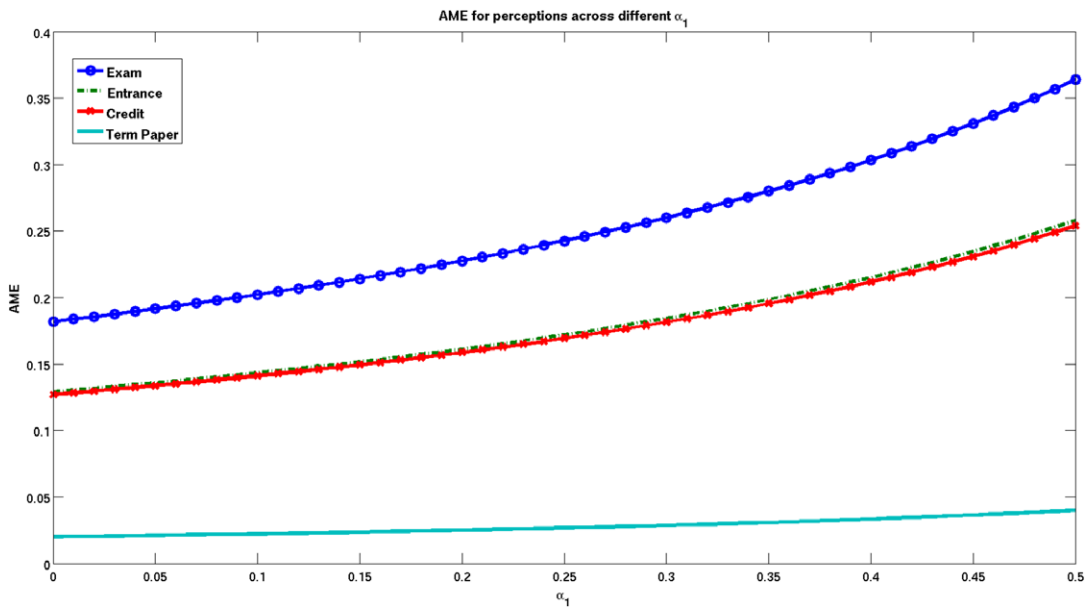
Results for Term Paper Bribes: Average Marginal Effects

	Nonparametric Specification				Probit Specification		
			95% CI			95% CI	
Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	**L.B.**	**U.B.**	$\widehat{\text{AME}}$	**L.B.**	**U.B.**
Corrupt	.239	**.020**	.009	.031	**.045**	.001	.089
Female	.222	−.009	−.019	.004	−.011	−.053	.032
Hard to Get Job	.000	−.019	−.039	.000	−.018	−.047	.011
Between 17 and 19	.154	−.009	−.025	.004	.009	−.071	.090
Over 19	.500	.000	.000	.000	.036	−.039	.111
Large City	.069	.019	−.001	.035	.040	−.005	.085
Medium City	.212	−.005	−.008	.000	−.029	−.065	.008
Small City	.132	**.031**	.015	.049	**.083**	.027	.139
Father in Private Sector	.000	−.003	−.026	.019	.000	−.036	.037
Father Is Cultural Worker	.500	.000	.000	.000	.008	−.029	.044
Father Not Working	.362	.002	−.002	.006	.018	−.028	.064
Crime	.227	−.007	−.019	.002	−.013	−.050	.023
Not Sure if Crime	.000	**−.030**	−.048	−.010	**−.030**	−.053	−.007
Gold Medal	.314	−.002	−.007	.003	−.015	−.040	.010
Past Briber	.166	**.023**	.009	.041	**.041**	.002	.081
Not Working	.498	.000	.000	.000	.013	−.043	.070

Results that are significant at the 5% level or greater are presented in bold.

FIGURE 1

Effect of Misclassification on AME for Perceptions across Different Types of Bribes



qualitatively summarize the results: Both corruption perceptions, attitudes toward the criminality of bribing, and past bribing behavior remain significant factors for bribing in all cases. The gender effect of female students reported in the above regressions is verified for bribing on term papers, but is not present for the other two types of bribes investigated. Further discussion of the nonparametric joint determination estimation results, including the relationship between different bribe types themselves, appears in Appendix A4.

Our results offer little support for the argument posed by Cabelkova and Hanousek (2004) on Ukraine that larger cities should experience higher levels of corruption as a result of greater anonymity and less social pressure to act morally. Instead we find a nonlinear relationship between city size and corruption. Our results suggest that students are more likely to bribe if they attend school in smaller cities while they are *less* likely to bribe if they attend school in an intermediate size city. If we think of larger cities as typically being more fractionalized ethnically, this result is in-line with the result of Cerqueti, Coppier, and Piga (2012), who show that the highest levels of corruption exist at the lowest and the highest levels of fractionalization. This induces a U-shaped relationship between corruption and fractionalization. Our results lend some support for this result under the assumption that smaller cities are less fractionalized than larger cities.

In addition, the results above suggest no relationship between parents' occupation and bribing. Similarly we find no evidence that job market prospects affect the propensity to bribe. Thus the hypothesis that students engage in corrupt practices in order to achieve better job market outcomes through the signaling process receives little support. Given this result one may be tempted to suggest that bribing is perhaps viewed simply as a cost of higher education as if it is "just the way things are done." Another possible explanation could be that the Ukrainian job market differentiates between university and high school education and thus students find it worth bribing for entrance and for passing courses, but not for "good" grades.

An interesting finding here is that women have a higher probability of bribing to enter an establishment and on term papers. This result is inconsistent with the literature surveyed in this article as it suggests that women are *more* corrupt than men. One might be tempted to argue that since women in Ukraine have faced deteriorating labor market conditions over the transition period as described by Brainerd (2000), female students perceive their job market prospects as relatively poorer. Hence they may bribe to ensure entrance into top schools or obtain better grades to further differentiate themselves in a discriminatory labor market. While this argument makes intuitive sense, the results suggest otherwise: If women's job market perceptions were the sole explanation for females' increased propensity to bribe for entrance or on term papers, then the female dummy variable should not have been significant after controlling for job market perceptions. As it indeed remains significant, there must be another explanation. Perhaps there exists discrimination against women in educational institutions which makes it relatively more difficult for them to succeed in an educational environment. As a result, they may be forced to bribe in order to receive treatment level with their male counterparts.

As in Swamy et al. (2001) and Svensson (2003), this study is using country specific data. We argue that our results are relevant and could be generalized to other former Soviet republics or countries with widespread corruption. Such generalization applies to the key explanatory variables for educational corruption identified in this study, i.e., criminality of bribing, perceptions of corruption, and past bribing behavior. Primarily, we argue that if one perceives corruption to be commonplace in educational institutions, it should impact the decision to engage in corrupt acts because perceptions signal the general level of acceptability of bribing. Given the finding of Swamy et al. (2001) that women are more likely to view bribing as never justified compared to men for the majority of the countries studied, however, it is hard to argue that our results on gender can be generalized to other countries.

V. CONCLUSION

This article examined the relationship between educational corruption and a set of potential explanatory variables using survey data from Ukraine. Corruption perceptions, past bribing behavior, and the perceived criminality of bribery were found to be significant factors with respect to bribing across all four categories of bribes examined, i.e., on an exam, for credit, on term papers, and for entrance. First, in agreement with Cabelkova and Hanousek (2004), perceptions of strong presence of corruption within an institution are associated with an increase in the probability of offering a bribe. Second, students who bribed during secondary education were found to have a greater probability of iterating this behavior at university. Third, believing or classifying bribing as a criminal act is associated with a lower probability of bribing across all four categories of bribery investigated. A number of other variables were investigated as possible relevant factors for corruption in tertiary education. However, none of them was robust across all specifications. In particular, females were found to have a greater probability to bribe only on an exam and for

entrance. Universities located in small cities were associated with a higher probability of bribing on an exam, for credit and on term papers, whereas those located in large cities appear to have a lower probability of bribing for entrance and credit.

If one were to interpret our results as causal, policy implications would follow from the insights gained in understanding what motivates corrupt behavior in the education sector. Our results indicate that awareness and education programs, such as the "rule of law" and "transparency and accountability" anti-corruption approaches advocated by Wood and Antonowicz (2011), are an appropriate combination for reducing the likelihood of student bribing in tertiary education institutions. First, as beliefs about the criminality of bribing are systematically important across all bribe types, efforts to educate and raise awareness on the legal implications of bribing are likely to reduce actual bribing occurrences. Better awareness includes instructing students on the implications of bribing behavior, as well as its legal consequences. Second, anti-corruption education program efforts targeted at changing corruption perceptions can be complementary to awareness campaigns in reducing actual corrupt behavior. From a policy perspective, when the enforcement of bribe control is difficult, targeting the transformation of perceptions could have a greater payoff than aiming at the direct reduction of corruption.

APPENDIX

A1. SIMULTANEOUS PROBIT

In the context of the generalized simultaneous probit model described in Section III.A, allowing for $\beta_{21} \times \beta_{12} \neq 0$ makes estimation of the model a bit more complex due to incompleteness. Incompleteness occurs when a set of values for $Z = [Z_1, Z_2]$ and $E = [e_1, e_2]$ result in overlapping outcomes for $Y = [Y_1, Y_2]$. As in Dagenais (1997) we can characterize incompleteness more effectively with the diagram presented in Figure A1.[7] The area R represents the values of Z and E that would result in indistinguishable outcomes $(Y_1 = 1, Y_2 = 1)$ and $(Y_1 = 0, Y_2 = 0)$. To rule out incompleteness, we follow the approach laid out by Chesher and Rosen (2012) which is a generalization of the parametric approach of Dagenais (1997). This approach amounts to restricting $g(E) = 0$ for $E \in R$. Where $g(E)$ is the joint density function for the unobservables. Note that we are not assuming the distribution of $g(E)$ is known, only that it is truncated to rule out incompleteness. Dagenais (1997) derives the likelihood function under the truncation assumption when the researcher is willing to assume that $g(E)$ takes a truncated bivariate normal distribution. Our nonparametric method described in Section III.B avoids placing restrictions on the functional form or on the type of distribution of the unobservables. In addition to this, we show in Section A3 of the appendix that our nonparametric approach is robust to the two types of endogeneity present under the bivariate and simultaneous probit frameworks.

7. Figure A1 only considers the case in which $\beta_{21} > 0$ and $\beta_{12} > 0$ which implies that students who bribe are more likely to think their institution is corrupt and vice versa.

A2. SPECIFICATION TESTING

To investigate whether misspecification is lurking within the standard probit model, we apply the Fan, Li, and Min (2006) nonparametric bootstrap test of conditional distributions for each of the four bribe types. This tests whether the true conditional distribution is different from that implied by the probit. The null hypothesis in Fan, Li, and Min (2006) is that the true population distribution is equal to some parametric conditional distribution given by $f(Y = y|X = x, \beta)$. Formally:

$$\text{(A1)} \quad H_0 : \Pr\left[f(Y = y|X = x) = f(Y = y|X = x, \beta)\right] = 1 \quad \text{for some} \quad \beta \in \Omega$$

In our case $f(Y = y|X = x, \beta) = yG(\beta x) + (1 - y)(1 - G(\beta x))$ where G is the standard normal cumulative distribution function. Rejection of the null hypothesis implies rejection of the probit specification. The probit model is rejected as correctly specified at the 1% significance level for bribing on exams and for entrance with p values of 0 and .001 respectively, and rejected at the 5% level for bribing for credit or passing a term paper with p values of .033 and .011, respectively. This leads us to conclude that the distribution of errors are misspecified under the probit model, the functional relationship between the variables is misspecified, or both the distribution and the functional form is misspecified. Consequentially, the standard probit model is inconsistent and statistical inference using it should be cautioned.

A3. MONTE CARLO SIMULATION

To demonstrate the power of our nonparametric approach, consider modeling bribing and corruption perceptions under a parametric framework:

$$\text{(A2)} \quad Y_1^* = \gamma_{01} + Z_1\gamma_1 + \beta_{12}Y_2 + e_1, \quad Y_1 = 1\left[Y_1^* > 0\right]$$

$$\text{(A3)} \quad Y_2^* = \gamma_{02} + Z_1\gamma_2 + \beta_{21}Y_1 + e_2, \quad Y_2 = 1\left[Y_2^* > 0\right]$$

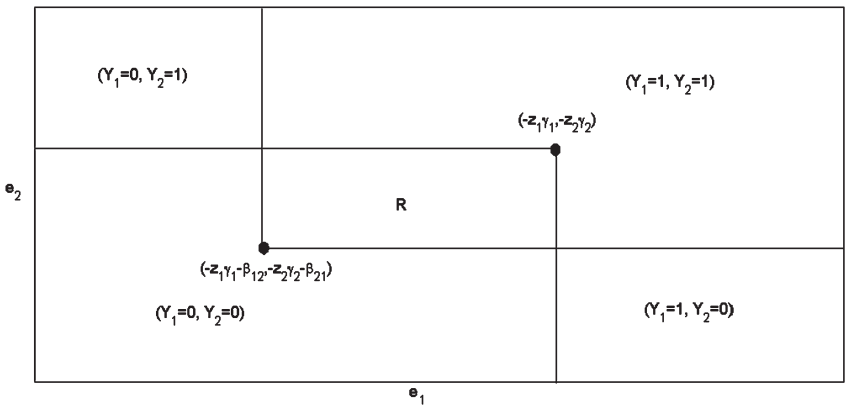
If we assume the errors are normally distributed with covariance $\rho = 0$ and $\beta_{21} = 0$, the probability of interest can be consistently estimated via a probit model so that:

$$\text{(A4)} \quad \Pr\left(Y_1 = 1|Y_2 = y_2, Z_1 = z_1\right) = G\left(\gamma_{01} + z_1\gamma_1 + \beta_{12}y_2\right)$$

where G is the standard normal cumulative distribution function. The problem with the probit model is that we could easily be wrong with respect to the distribution of the errors. In addition, we could also incorrectly specify the underlying index function. There may be interaction terms that might be easily excluded in favor of a more parsimonious model. Another possible specification that we should consider is that of a bivariate probit. It might be true that the unobservables in Equations (A2) and (A3) are related so that $\rho \neq 0$. Under this specification the probit model is no longer consistent for the

FIGURE A1

The Area *R* Represents the Area of Overlap with $\gamma_{01} = \gamma_{02} = 0$



marginal effect. For example, suppose that we model corruption perceptions as:

$$\text{(A5)} \qquad Y_2^* = \gamma_{02} + Z_1\gamma_2 + e_2, \;\; Y_2 = 1\left[Y_2^* > 0\right].$$

Given we assume a bivariate normal distribution with correlation ρ, it can be shown that the marginal effect of Y_2 on Y_1 is equal to:

$$\text{(A6)} \qquad \theta\left(z_1\right) = \frac{\int_{-(\gamma_{02}+z_1\gamma_2)}^{\infty} G\left[\frac{\gamma_{01}+x_{(1)}\beta+\rho v}{\sqrt{1-\rho^2}}\right] f(v)\,dv}{G\left(\gamma_{02}+z_1\gamma_2\right)} - \frac{\int_{-\infty}^{-(\gamma_{02}+z_1\gamma_2)} G\left[\frac{\gamma_{01}+x_{(0)}\beta+\rho v}{\sqrt{1-\rho^2}}\right] f(v)\,dv}{1-G\left(\gamma_{02}+z_1\gamma_2\right)}$$

$$= \frac{P\left[Y_1 = 1, Y_2 = 1|z_1\right]}{P\left[Y_2 = 1|z_1\right]} - \frac{P\left[Y_1 = 1, Y_2 = 0|z_1\right]}{P\left[Y_2 = 0|z_1\right]}$$

where $x_{(1)}$ and $x_{(0)}$ are constructed such that y_2 is set to one and zero, respectively. To obtain this marginal effect, one would have to construct the likelihood function under the bivariate specification and then maximize with respect to the model parameters. Furthermore if we assume $\rho \neq 0$ and $\beta_{21} \neq 0$, we can construct a likelihood function for the simultaneous probit as presented in Dagenais (1997) under a truncated bivariate normal distribution.

To investigate the performance of the nonparametric approach, we generate a hypothetical model under univariate, bivariate, and simultaneous probit specifications for a sample size of 1588 over 5000 Monte Carlo simulations. For the simulation we generate the following functional specifications:

$$\text{(A7)} \qquad Y_1^* = .5Z_1 + .5Y_2 + e_1, \;\; Y_1 = 1\left[Y_1^* > 0\right]$$

$$\text{(A8)} \qquad Y_2^* = .5Z_1 + \beta_{21}Y_1 + e_2, \;\; Y_2 = 1\left[Y_2^* > 0\right]$$

TABLE A1
Exam Bribes with Joint Determination of Bribes

			95% CI	
Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	**L.B.**	**U.B.**
Corrupt	.090	**.134**	.096	.162
Female	.500	.000	.000	.000
Hard to Get Job	.500	.000	.000	.000
Between 17 and 19	.500	.000	.000	.000
Over 19	.210	−.015	−.031	.004
Large City	.500	.000	.000	.000
Medium City	.040	.009	−.023	.041
Small City	.039	.086	.037	.132
Father in Private Sector	.370	−.005	−.014	.003
Father Is Cultural Worker	.500	.000	.000	.000
Father Not Working	.500	.000	.000	.000
Crime	.326	**−.014**	−.024	−.002
Not Sure if Crime	.000	−.009	−.053	.046
Gold Medal	.294	.009	−.002	.020
Past Briber	.166	**.034**	.008	.062
Not Working	.500	.000	.000	.000
Enter	.129	**.077**	.047	.103
Credit	.047	.022	−.015	.062
Term	.000	**−.083**	−.129	−.041

Results that are significant at the 5% level or greater are presented in bold.

with $Z_1 d \sim N(0, 1)$. We generate the error structure as follows:

$$\text{(A9)} \qquad \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} d \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$$

when $\beta_{21} = 0$ we have a univariate probit when $\rho = 0$ and a bivariate probit when $\rho \neq 0$. We also report results for $\rho \neq 0$ and β_{21}=.5 which corresponds to a simultaneous probit. To ensure the simultaneous probit is complete, we generate the data so that error distribution is truncated as required in Dagenais (1997). In Figure A2 we graph the distribution of the nonparametric marginal effect against the true marginal effect under each of the specifications. It is clear from the graph that

FIGURE A2

Monte Carlo Distribution for Nonparametric Marginal Effect. (a) Univariate Probit Specification, (b) Bivariate Probit Specification, (c) Simultaneous Probit Specification

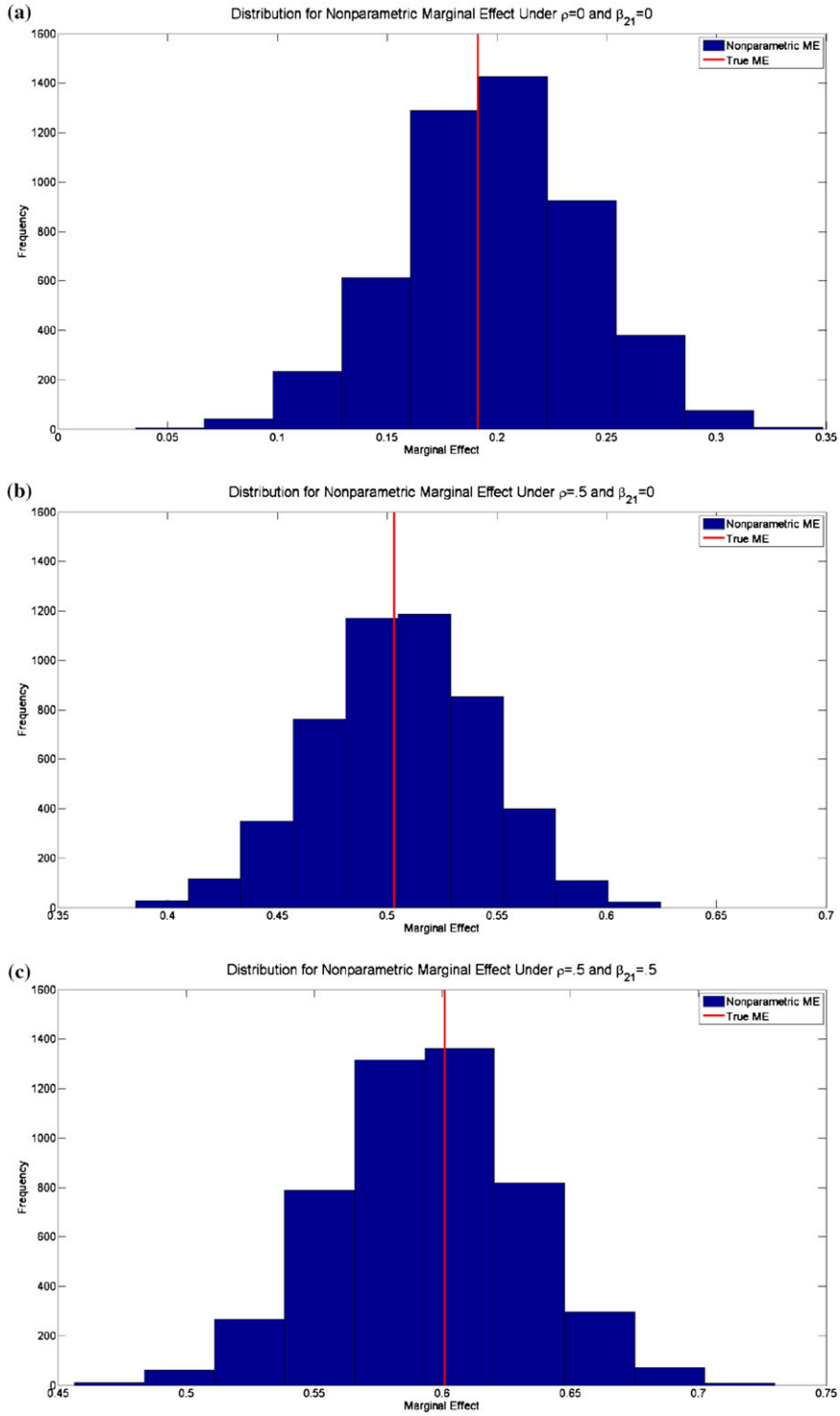


TABLE A2
Credit Bribes with Joint Determination of Bribes

Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	95% CI L.B.	95% CI U.B.
Corrupt	.106	**.126**	.092	.164
Female	.500	.000	.000	.000
Hard to Get Job	.293	.001	−.014	.017
Between 17 and 19	.500	.000	.000	.000
Over 19	.291	−.013	−.026	.000
Large City	.273	−.009	−.023	.007
Medium City	.000	−.002	−.062	.070
Small City	.122	.058	.026	.092
Father in Private Sector	.427	−.004	−.009	.000
Father Is Cultural Worker	.101	.000	−.032	.036
Father Not Working	.500	.000	.000	.000
Crime	.373	**−.011**	−.021	−.001
Not Sure if Crime	.470	.000	−.001	.002
Gold Medal	.500	.000	.000	.000
Past Briber	.208	**.025**	.003	.050
Not Working	.500	.000	.000	.000
Exam	.003	**.119**	.077	.158
Enter	.208	.013	−.010	.030
Term	.012	**−.048**	−.088	−.001

Results that are significant at the 5% level or greater are presented in bold.

TABLE A3
Term Paper Bribes with Joint Determination of Bribes

Variable	$\hat{\gamma}_2$	$\widehat{\text{AME}}$	95% CI L.B.	95% CI U.B.
Corrupt	.161	**.112**	.085	.136
Female	.280	**.023**	.006	.034
Hard to Get Job	.000	.004	−.033	.044
Between 17 and 19	.500	.000	.000	.000
Over 19	.249	−.014	−.026	.004
Large City	.091	−.026	−.055	.009
Medium City	.389	.002	−.002	.007
Small City	.074	.064	.019	.103
Father in Private Sector	.253	−.009	−.025	.011
Father Is Cultural Worker	.493	.000	.000	.000
Father Not Working	.500	.000	.000	.000
Crime	.203	**−.025**	−.045	−.006
Not Sure if Crime	.000	−.004	−.057	.040
Gold Medal	.324	.010	−.003	.019
Past Briber	.203	**.029**	.009	.050
Not Working	.500	.000	.000	.000
Exam	.057	**.105**	.067	.142
Enter	.500	.000	.000	.000
Credit	.067	−.016	−.038	.011

Results that are significant at the 5% level or greater are presented in bold.

regardless of the specification, the nonparametric estimate is centered around the true marginal effect.

A4. JOINT DETERMINATION ESTIMATION

Tables A1–A3 present the results for the nonparametric estimation of the joint determination of bribes. In agreement with the results of the primary specification, students who perceive their institution to be corrupt and those who bribed in the past are more likely to pay a bribe on an exam, for credit, and on a term paper. In addition, when bribing is considered a criminal act the probability of bribing is lower.

With this model, we also obtain insights into the relationship between different bribes. In particular, while bribing for entrance increases the probability of bribing on exams, it is found to have no statistically significant effect on other bribing behavior. Students who bribed on a term paper are *less* likely to bribe on an exam, whereas students who bribed on an exam are *more* likely to bribe on a term paper. A possible interpretation of this seemingly non-intuitive or contradictory finding lies on the timing and the sequence of the events. Although exams occur regularly throughout the duration of a course, term papers are typically due at the end of the semester. Thus, a student who bribes on an exam could adopt this habit throughout the whole course and bribe again on their term paper. However, a student who refrained from bribing on exams throughout the semester may eventually find it necessary to bribe on a term paper in order to "keep up with the corrupt Joneses."

Similarly, we find that a student is *less* likely to bribe for credit if they bribed on a term paper while more likely to bribe for credit if they bribed on an exam. Again, these two seemingly contradictory findings could lie on the fact that a student who tries to build up a "good" grade on a certain course, may entertain bribing on several occasions throughout the semester to achieve this goal. However, bribing only on a term paper will most likely result in a grade just sufficient for passing a course. The difference in the main incentive of the student could thus be driving this result.

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