

# Admission is Free Only if Your Dad is Rich!

## Distributional Effects of Corruption in Schools in Developing Countries

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### ABSTRACT

In the standard model of corruption, the rich are more likely to pay bribes for their children's education, reflecting higher ability to pay. This prediction is, however, driven by the assumption that probability of punishment for bribe taking is invariant across households. In many developing countries lacking in rule of law, this assumption is untenable, because the enforcement of law is not impersonal or unbiased and the poor have little bargaining power. In a more realistic model where the probability of punishment depends on household's economic status, bribes are likely to be regressive, both at the extensive and intensive margins. Using rainfall variations as instrument for household income in rural Bangladesh, we find strong evidence that corruption in schools is doubly regressive: (i) the poor are more likely to pay bribes, and (ii) among the bribe payers, the poor pay a higher share of their income. The results indicate that progressivity in bribes reported in the earlier literature may be due to identification challenges. Our OLS regressions show that bribes increase with household income, but the IV estimates suggest that the OLS results are spurious, driven by selection on ability and preference. The evidence reported in this paper implies that 'free schooling' is free only for the rich, and corruption makes the playing field skewed against the poor. This may provide a partial explanation for the observed educational immobility in developing countries.

**Key Words:** Corruption, Bribes, Education, Schools, Inequality, Income Effect, Bargaining Power, Regressive Effects, Educational Mobility

**JEL Codes:** O15, O12, K42, I2

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## Introduction

The experience in many developing countries over last few decades shows that economic liberalization delivered high income growth and impressive poverty reduction, but it also resulted in a significant increase in inequality and corruption (see, for example, World Development Reports (1997, 2004, 2006)).<sup>2</sup> While a variety of factors such as returns to entrepreneurial risk taking and skill biased technological change contributed to the rise in inequality, there is also a growing recognition that a significant part of the observed rise in inequality may be of “wrong kind”, reflecting and reinforcing inequality of opportunities across generations, and driven, at least partly, by pervasive corruption. There is a widespread perception among general people that the fruits of economic growth have been skewed in favor of the rich, and the playing field is not level.<sup>3</sup>

The relevant policy question is how to reduce inequality without stifling the dynamism of a liberalized economy that rewards effort and entrepreneurial experimentation? There is a broad consensus in the academic literature and among the policy makers that education is among the most important policy instruments in this regard. For example, Stiglitz (2012, P. 275) notes “(O)ppportunity is shaped, more than anything else, by access to education”, and Rajan (2010, P.184) argues “..the best way of reducing unnecessary income inequality is to reduce the inequality in access to better human capital”. A focus on building the human capital of the poor seems triply desirable: (i) it is the only asset that every poor ‘owns’, (ii) human capital is inalienable and thus less susceptible to expropriation, an important advantage in many developing countries suffering from a lack of rule of law, and (iii) returns to education are expected to increase over time with globalization because of skill-biased technological change. Recognizing this unique role of education, a large number of developing countries over the last few decades invested heavily on policies such as free universal schooling (at least at the primary level), scholarships for girls, free books, and mid-day meals. The basic assumption is that such policies would lessen the burden on poor families for educating their children, and thus help reduce educational and income inequality and improve economic mobility of the children from poor families.

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<sup>2</sup>World Development Reports: Equity and Development (2006), Making Services Work for Poor People (2004), and The State in a Changing World (1997).

<sup>3</sup>A recent survey by Pew Global attitudes project in China conducted in March and April of 2012 finds that about half of the respondents identified increasing income inequality and corruption as “very big problem”, while 80 percent agree with the view that “rich just get richer while the poor get poorer.”

However, corruption is endemic in schools in developing countries (see various annual and country reports by Transparency International). In Bangladesh about half of the households reported paying some form of bribe for children’s education (Transparency International Bangladesh, 2010). Evidence from a seven country study in Africa by World Bank shows that 44 percent of parents had to pay illegal fees to send their children to school (see World Bank (2010)).<sup>4</sup> According to a New York Times report, bribery is rife not only in school admissions in China, even the front row seats in the classroom are up for sale!<sup>5</sup> The focus of this paper is on the following question: how does corruption in schools in the form of bribes paid for educational services such as admission, stipend etc. affect poor families? We provide evidence that bribe taking by teachers in schools affects poor households disproportionately; poor parents are more likely to pay bribes for education of their children, and among the bribe payers, the poor pay more as a share of their income. This is a perverse outcome, opposite to the goal of making education free for the poor. The ‘free’ schooling seems free only for the richer households as they are not likely to pay bribes, while the poor still pay for their children’s schooling.<sup>6</sup>

To guide the empirical work, we use a simple model of bribe taking by teachers in a context where households are heterogenous in terms of their economic status as measured by income.<sup>7</sup> An important assumption in many corruption models is that the probability and the severity of punishment for taking bribes are determined by an impersonal and unbiased legal and enforcement system. This delivers the prediction that bribes are progressive at the extensive margin, i.e, the poor are less likely to be asked for (and pay) bribes. However, the assumption that the ability to punish a corrupt teacher does not vary across poor and rich households is clearly at odds with reality in a developing country.<sup>8</sup> Because higher income (and wealth) confers significant social and political influence on a household in a developing country, and the rich can inflict

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<sup>4</sup>The countries in the study are: Ghana, Madagascar, Morocco, Niger, Senegal, Sierra Leone and Uganda.

<sup>5</sup>“A Chinese Education, for a Price”, New York Times, November 21, 2012.

<sup>6</sup>It is important to appreciate that bribery in public schools is thus more regressive than a market based education system. In a marketplace, everyone pays the same price, irrespective of their economic status, under the plausible assumption that school fees are not used for price discrimination according to ethnicity, income etc.

<sup>7</sup>Note that our framework is designed for the analysis of bribery faced by households, and may not be suitable for understanding bribery faced by firms.

<sup>8</sup>For an interesting discussion on the role played by socioeconomic status in determining who pays bribes to traffic police in Afghanistan, see Azam Ahmed’s article titled “In Kabul’s ‘Car Guantánamo,’ Autos Languish and Trust Dies” in New York Times dated February 17, 2013. Ahmed writes “The rules are unevenly applied, *punitive to those who can least afford it, and mostly irrelevant to those with money and power*” (*italics added*).

substantial social and economic costs on a teacher if she asks for bribes (including anti-corruption investigation and prosecution). The higher bargaining power of the richer households thus may allow them to avoid paying bribes altogether.<sup>9</sup> For example, the village school teacher may not risk *asking* for bribes for admission of the daughter of a local political leader or landlord, even though a political leader or landlord has higher ability to pay. Alternatively, a household with high bargaining power may choose to *refuse to pay* when a bribe demand is made, and still get the child admitted into the school.<sup>10</sup> The implications of higher bargaining power associated with higher income in understanding the distributional consequences of corruption is a central focus of this paper. It is important to emphasize that we are not estimating the standard ‘income effect’, our focus is on the effects of higher income when income plays double roles: it represents ability to pay (income effect), and it is also an indicator of a household’s bargaining power that captures, among other things, social and political connections.<sup>11</sup> We model the bargaining power effect as a higher probability of punishment for a corrupt teacher when asking for bribes from a richer household. If the bargaining power effect of household income is strong enough, higher income reduces the propensity to pay bribes; the teacher does not ask for bribes from richer households, thus making bribery regressive at the ‘extensive margin’.

Another important question is whether bribery in schools in developing countries is likely to be progressive at the intensive margin, i.e., among the bribe payers, who pays more, rich or poor? In the standard model above, bribes are ‘weakly progressive’, i.e., the amount of bribes paid increases with income when two conditions are met: (i) the teacher has information about household income, and (ii) household utility function is strictly concave. Strict concavity of the utility function, however, is necessary but not sufficient for bribes to be progressive in the standard sense familiar from the tax literature, i.e., bribes as a share of income to increase with the level of income. We show that additional restrictions on the curvature of the utility function

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<sup>9</sup>One may also call it ‘countervailing power’. For brevity, we use the term ‘bargaining power’.

<sup>10</sup>The existing literature on corruption focuses on the bargaining game after a teacher asks for bribes, with refusal to pay (zero share of the surplus for the teacher) being one possible outcome. However, the possibility that the teacher may not even ask for bribes when facing a high income household has not been adequately appreciated. The role played by ‘refusal power’ in determining who pays bribes in the context of firms has been highlighted by Svensson (2003).

<sup>11</sup>As explained later in more details, the part of social and political capital of a household which is orthogonal to income becomes part of the error term in our framework. However, it does not bias the estimated effect of income precisely because it is not correlated with income.

are required to obtain standard progressivity at the intensive margin. Thus even when the corrupt official can extract the total surplus from a household, there is no presumption that bribes will be progressive. As is well-known in the literature, if the teacher does not have adequate information to price discriminate, then the bribe amount is not likely to vary with income, making it regressive at the intensive margin. The stringency of the conditions needed for bribes to be progressive in the standard sense has not been well-appreciated in the existing literature.

There are two major challenges in the empirical estimation and testing of the above hypotheses. First, unobserved heterogeneity in preference and ability. A household's attitude/preference towards corruption is unobservable to an empirical economist but may be correlated with its income. For example, people with a low moral cost of corruption may become rich through corrupt economic activities, and they are also more likely to bribe a school teacher to get their children admitted to the schools. Any positive effect of income on the probability of paying bribes for admission estimated in an OLS regression may be driven by this selection on unobserved preference. High ability parents in general have higher income and may also have high ability children due to genetic transmissions. The high-ability parents may be more willing to pay bribes for education of their children, because they expect higher returns from the labor market. The second important source of bias is measurement error in income (or other indicators of economic status of a household) which might cause significant attenuation bias. To address these identification challenges, we employ an instrumental variables strategy that exploits *ten-year average rainfall variations* across different villages as a source of exogenous variation in household income. Rainfall is obviously an important exogenous determinant of household income in rural areas of developing countries. The identifying assumption that rainfall affects household income significantly but is uncorrelated with ability (genetically transmitted), moral preference regarding corruption and the measurement error in household income seems eminently plausible. For example, to the best of our knowledge, there is no theoretical basis or empirical evidence to expect that heavy rainfall directly affects people's moral compass with respect to corruption, or determines children's cognitive ability, after taking into account its effects through income.<sup>12</sup> We report results from

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<sup>12</sup>We use a binary indicator of 'heavy rainfall' as the main identifying instrument for household income. A Google Scholar and Econlit search on December 20 2012 for different combinations of keywords 'rainfall', 'scholastic ability', 'ability', 'smart', 'corruption', 'corrupt', 'attitude' returned no relevant entries. An advantage of a binary instrument is that it necessarily satisfies the monotonicity condition of Imbens and Angrist (1994).

a falsification exercise and a detailed discussion on the potential objections to our identification strategy below in section (4.1).

As additional evidence, we use interaction of rainfall with exogeneous household characteristics such as age and religion of household head as identifying instruments.<sup>13</sup> This is motivated by the observation that the effects of heavy rainfall are likely to vary across households; a younger household head is probably more equipped to deal with adverse weather shocks, for example, by temporary migration to the nearest town for work, and effectiveness of informal risk sharing may vary across different religious groups. To strengthen the exclusion restriction imposed on the interaction of heavy rainfall, we follow Carneiro et al. (forthcoming) and control for possibly nonlinear direct effects of age and religion in the IV regressions. The estimates from alternative instruments provide robust evidence on the effects of household income on the propensity to bribe and amount of bribe payments. For an in-depth discussion of our approach to identification, please see pp. 13-21 below.<sup>14</sup>

The empirical results from the instrumental variables approach find a statistically significant effect of income on propensities to bribe, but *not* on the amount of bribe paid. Income has a significant and *negative* effect on the probability of paying bribes, providing credible evidence that rich are less likely to pay bribes, possibly because of their superior bargaining power. The evidence from IV regressions that finds no statistically significant effect of income on the amount of bribes suggests a lack of ‘price’ discrimination; thus poor pay more as a share of their income. This conclusion is especially noteworthy, because the OLS regressions stand in sharp contrast, showing a *significant positive* effect of income on the amount of bribes paid. This seems to justify the worry that the OLS regressions may be susceptible to finding spurious progressivity in the burden of bribery (or at least under-estimate the degree of regressiveness), due to ability and preference heterogeneity.

Rest of the paper is organized as follows. Section (2) discusses the related literature and thus help put the contributions of this paper in perspective. The next section provides a con-

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<sup>13</sup>Religion is determined by birth for almost everyone, as conversion is extremely rare.

<sup>14</sup>Some of the potential objections to identification are: (i) rainfall may affect the child wage and thus demand for schooling, (ii) heavy rainfall may cause damage to schools and thus increase the demand for local resources, (iii) heavy rainfall may affect health. We provide evidence on the (in)validity and/or irrelevance of these and other objections in section (4.1) below.

ceptual framework to guide and interpret the empirical work. The empirical strategy to address the potential biases from household heterogeneity and measurement error is discussed in section (4). The next section (section (5)) provides a discussion of the data sources and variables. The OLS results are reported in section (6) and the IV estimates in section (7). Section (8) reports robustness check for the IV results and section (9) discusses the interpretation of the IV estimates. The paper concludes with a summary of the results and their implications for the broader debate about the role of public schooling and anti-corruption measures to address inequality in educational opportunities.

## (2) Related Literature

The economics literature on corruption is substantial and has been the focus of innovative research in the last decade. For recent surveys of the literature, see, for example, Olken and Pande (2011), Banerjee et al. (2012), Rose-Ackerman (2010), Bardhan (1997).<sup>15</sup> The literature has, for good reasons, focused on the measurement of corruption, its effects on efficiency, and on policies to combat corruption in different contexts.<sup>16</sup>

The literature on the effects of corruption on households is, however, rather limited; for example, the recent survey by Olken and Pande (2011) discusses only one paper (Hunt, 2007) that provides evidence on the effects of corruption on households when they face negative shocks. The available evidence on the heterogeneity in the burden of corruption is, however, mixed, which may, at least partly, reflect the difficulties in identification arising from unobserved heterogeneity and measurement error. Kauffman et al. (1998), and Kauffman et al. (2005) reported bribes to be regressive as the poor pay a higher share of their income as bribes. On the other hand, Hunt (2010) reports evidence suggesting that corruption in health care in Uganda is progressive both at the intensive and extensive margins. Hunt and Laszlo (2012) find that bribery is not regressive in Uganda and Peru. Hunt (2008) shows that the distributional effects of bribes in Peru depend on

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<sup>15</sup>The early contributions to corruption literature include Rose-Ackerman (1978), Klitgaard (1988), Shleifer and Vishny (1993).

<sup>16</sup>For recent contributions on measurement, see, for example, Fisman (2001), Reinikka and Svensson (2004), Olken (2009), Olken and Barron (2009) and Banerjee and Pande (2009), Hsieh and Moretti (2006), Besley et al. (2011), Niehaus and Sukhtankar (2010); for contributions on costs of corruption, see, among others, Svensson (2003), Fisman and Svensson (2007), Bertrand et al. (2007), Ferraz, Finan, and Moreira (2012), Sequeira and Djankov (2010), Olken (2006, 2007, 2009), and on policies to combat corruption, see, for example, Di Tella and Schargrodsky (2004), Niehaus and Sukhtankar (2010), Olken (2007), Bjorkman and Svensson (2010), Banerjee et al. (2012), Kahn et al. (2001).

the public service one considers. She finds that bribery is regressive for users of police service, but it is progressive for users of the judiciary. Mocan (2008), using household data from a number of countries, shows that the higher income households are more likely to face a demand for bribe in developing countries, but the effect is not significant in developed countries.<sup>17</sup> In an important paper on corruption faced by firms, Svensson (2003) carefully considers the identification issues, and finds that bribe amount paid by firms in Uganda increases with its profit (“ability to pay”). However, the slope of the bribe function, although positive, is not steep.

With the exception of Hunt and Laszlo (2012) and Svensson (2003), much of the evidence on the relationship between the bribe amount and household income (or firm profit) is based on OLS regressions; they do not address the biases due to unobserved heterogeneity and measurement errors. In the context of corruption faced by households, Hunt and Laszlo (2012) take a step forward and correct for the biases due to measurement error by using household wealth indicators as instruments, but their strategy is not designed to tackle the omitted variables bias arising from unobserved heterogeneity in preference and ability.

### **(3) Conceptual Framework**

To guide the empirical work, we use a simple model of bribery for admission into school. The focus of our analysis is on two things: (i) to understand under what conditions we can expect bribes to be progressive (or conversely, regressive), and (ii) to sort out the implications of alternative assumptions regarding bargaining power and information structure for the empirical analysis. We discuss progressivity both at the extensive and intensive margins. If bribes are progressive at the extensive margin, the probability that a household pays bribes for education of its children should be lower for the low-income households. At the intensive margin, the standard definition of progressivity requires that the rich pay more as a proportion of their income among the subset of bribe payers. A weaker definition of progressivity at the intensive margin is when bribes are a strictly positive function of a household’s income.

The teacher has two sources of income: salary  $w$  received from employment in public schools,

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<sup>17</sup>It has been noted in the literature that the rich may be more likely to pay bribes, because they enjoy more public services (Hunt and Laszlo (2012), Mocan (2008)). For example, most of the poor never face the possibility of paying bribes for a passport, because they do not travel internationally. It is thus important to focus on a given service that is used by both rich and poor (schooling in our case) to better understand the distributional consequences of bribes.

and bribes for admitting students to school. The households in the village are heterogenous in terms of their economic status as measured by income  $y_i$  and bargaining power  $\sigma_i$ . The probability of punishment for asking bribes from household  $i$  is  $\delta(\sigma_i)$ , and we assume that the probability is increasing in the bargaining power of the household. The bargaining power depends on income and also a set of factors uncorrelated with income  $\psi_i$ , i.e.,  $\sigma_i = \sigma(y_i, \psi_i)$ .  $\sigma_i$  is increasing in both its arguments. The assumption that the bargaining power  $\sigma_i$  is a positive function of household income captures the idea that the rich have better bargaining power. The functions  $\delta(\cdot)$  and  $\sigma(\cdot)$  are common knowledge. If caught and convicted of corruption, the school teacher loses her job, thus payoff is zero in this case.

Income of household  $i$  is a function of its resource endowment  $E_i$  and ability of parents  $A_i^f$ . The households also vary in terms of their moral costs of corruption (measured in terms of utility loss)  $M_i \in [M_L, M_H]$ . The income function is

$$y_i = y(E_i, A_i^f, M_i) \text{ with } \frac{\partial y(\cdot)}{\partial E_i} > 0; \frac{\partial y(\cdot)}{\partial A_i^f} > 0; \frac{\partial y(\cdot)}{\partial M_i} < 0 \quad (1)$$

So household income is increasing in its endowment and parental ability, but is a negative function of moral cost  $M_i$ . A household with low moral cost can profit from corrupt deals and activities, for example, by getting a contract through bribing. For simplicity,  $y_i$  is assumed to be discrete and households are ordered according to income as  $y_0 < y_1 < \dots < \bar{y}$ . Each household has one school aged child. All students receive the same quality of education at school, and hence class room instructions is a public good. The quality of education received by a student  $i$  is  $q(A_i)$  where  $A_i \in [A_L, A_H]$  is the ability of the child. The human capital function  $q(A_i)$  is strictly increasing in ability.

In addition to possible bribes to teachers, a household spends its income on a consumption good  $c$ . Following the literature, we assume that utility takes the following form:

$$V_i = q(A_i) + u(c_i - B_i) - M_i \quad (2)$$

where  $u(\cdot)$  is assumed to be increasing and strictly concave, and  $B_i \geq 0$  is the amount of bribe. Admission into school ensures human capital  $q(A_i)$ .

We consider the following sequence of events. First, the teacher decides whether to ask for bribes from household  $i$  based on the estimate of probability of punishment given the information set  $\Omega$ . We will discuss the implications of different assumptions regarding the information set below. Denote the probability estimate by  $\hat{\delta}(\Omega)$ . If s/he decides to ask for a bribe, the teacher makes a take-it-or-leave-it offer to the parents. The parents decide whether to accept the bribe demand, or reject by deploying their ‘bargaining power’. The teacher decides whether to admit the child into the school.

**Bribe Determination When Teacher Has Perfect Information and the Probability of Punishment is Constant**

We first consider a set-up where legal and enforcement systems are impersonal, and the households do not vary in terms of their bargaining power and the common probability of punishment faced by the corrupt teacher across different households is  $\tilde{\delta}$ . We also assume that the teacher observes income, and the type of a household in terms of ability and moral preference, i.e, the information set  $\Omega = (y, A^f, A, M, \tilde{\delta})$ . This is a useful benchmark, conducive to obtaining a progressive burden of bribes on the households, both at the intensive and extensive margins.

Consider a household’s decision as to whether to pay bribe or not for school admission when the teacher makes a take-it-or-leave-it bribe demand. Given that the household cannot influence the probability of punishment, it is optimal for a household to pay bribe to get admission for its kid into the school if the bribe demand  $B_i$  satisfies the following:

$$q(A_i) + u(y_i - B_i) - M_i \geq u(y_i) \tag{3}$$

The main results that follow from the above benchmark model are summarized in proposition (1) below.

### Proposition 1

Assume that the teacher has perfect information and makes a take-it-or-leave-it bribe demand. In this case the participation constraint (3) binds for each household that sends a child to school.

(1.a) Bribery is progressive at the extensive margin in the sense that there exists a threshold income  $\tilde{y}$  such that a household with income  $y_i < \tilde{y}(A_H, M_L)$  is not asked for any bribe for admission.

(1.b) There exists a threshold income  $y^L(A_H, M_L)$  below which a household is unwilling to pay a positive (however small) bribe for admission.

(1.c) Among the households with a child in school, the bribe amount is a positive function of income if the household utility function is strictly concave. In other words, bribe is ‘weakly progressive’ at the intensive margin.

(1.d) Bribes are progressive at the intensive margin (i.e., the bribe as a share of income increases with the level of income) only if the utility function exhibits strong enough concavity.

#### Proof:

Omitted. See online appendix.

Variants of propositions (1.a)-(1.c) have been discussed in the literature before, but proposition (1.d) is new, to the best of our knowledge. Proposition (1.d) shows that even with perfect information, the maximum bribe a teacher can extract is not progressive if the curvature of the utility function is not strong enough. With an isoelastic utility function, it can be shown that the bribes are progressive in the standard sense only if the utility function has more curvature than a log function (see the online appendix). This result is simple, but important, because most of the literature on the distributional burden of corruption uses the standard notion of progressivity borrowed from the tax literature, and the stringency of the conditions required for such progressivity in the context of bribery is in general not well appreciated. A weaker notion of progressivity where the bribes are a strictly positive function of income seems more plausible in this context.<sup>18</sup>

### Alternative Information Assumptions

The benchmark model above assumes that the teacher has enough information on all the

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<sup>18</sup>The weaker notion is employed in some of the existing studies such as Svensson (2003).

relevant household characteristics to price discriminate perfectly and extract the full surplus. Many readers may find this assumption unrealistic even in the context of a static village economy, especially the assumption that the bargaining power, corruptibility, ability are observable may be too strong. The other polar assumption standard in many corruption models that the official does not observe any indicator of income, ability, and moral preference, and thus has to charge a uniform bribe is probably equally unrealistic in the context of villages and small towns in developing countries.

An intermediate information assumption is that the teacher observes only income, but does not observe any other indicators of ability, moral preference, or bargaining power. In this case, the teacher relies on income information to infer unobserved bargaining power. We develop a model below that captures the notion that higher income is positively correlated with higher bargaining power, and thus the probability of paying bribes is lower. In what follows we adopt this intermediate information assumption, if not otherwise indicated. When discussing the empirical results we also note the implications of the fact that a teacher will in general ‘observe’ household income with some error.

### **Heterogeneity in Bargaining Power and Probability of Punishment**

As noted before, to capture the idea of higher ‘bargaining power’ of richer households, we assume that a teacher faces higher probability of punishment when asking for bribes from a higher income household. We emphasize again that we use the term ‘bargaining power’ as a portmanteau term that represents their own social and political influence and the “connections” that come with higher income and wealth in a developing country. To simplify and focus on the role played by a household’s bargaining power vis a vis the teacher, we assume in this section that the households do not vary in terms of ability or moral costs.

Since the teacher observes only income of a household, it estimates the bargaining power of a household as  $\hat{\delta}_i = \hat{\delta}(y_i, E(\psi_i))$ . Since  $\psi_i$  is not observed by the teacher the mean value  $E(\psi_i)$  is used. So the estimated probability of punishment is  $\hat{\delta}_i(y_i) = \delta(\sigma(y_i, E(\psi_i)))$ . We assume that there are lower ( $\hat{y}_l$ ) and upper ( $\hat{y}_h$ ) thresholds of income such that  $\hat{\delta}(y_i) = 0$  for  $(y_i \leq \hat{y}_l < y_0)$  and  $\hat{\delta}(y_i) = 1$  for  $(y_i \geq \hat{y}_h < \bar{y})$ . Thus we assume that the poorest of the households have no bargaining power, while the richest ones can punish the teacher for bribe taking with probability

1. Note that once the teacher decides to ask for bribes from a household, it is optimal for her to extract full surplus from the household, because the probability of getting caught and punished does not depend on the bribe size.

The central result from the above set up is that bribery is likely to be regressive at the extensive margin if the bargaining power effect is strong enough. Given the assumptions regarding the probability estimate, it follows that there exists a threshold  $y^M < \bar{y}$ , such that the following equality holds (assuming that the teacher maximizes expected income):

$$\left\{1 - \hat{\delta}(y^M)\right\} [B^*(y^M) + w] = w \quad (4)$$

Now it is easy to check that if the bargaining power effect of income is strong enough in the sense that  $\hat{\delta}'(y)$  is greater than a threshold, the teacher does not ask for bribes from any household with income higher than the threshold  $y^M$  (see the online appendix). The model thus predicts that when the bargaining power effect of income is strong enough, among all households with the child in school, only the relatively poor pay bribes, the richer households ( $y_i > y^M$ ) are not asked for bribes, even though they have better ability to pay. Thus bribes are clearly regressive in this case, a sharp contrast to the results in proposition (1).

Now consider a household  $j$  with income  $y_j < y^M$ , but  $\psi_j > E(\psi_i)$  such that the teacher underestimates the true bargaining power and asks for bribes. But if  $\psi_j$  is high enough so that  $\delta(\sigma(y_j, \psi_j)) \geq \hat{\delta}(y^M)$ , it is in the best interest of the household to deploy its social connections (for example, a call from the office of the education minister, who happens to be the brother of the household head's primary school buddy). In this case, assuming that the household can credibly communicate its true bargaining power, it will refuse to pay the bribe, but still get the child admitted in the school. For our empirical analysis, this has important implications in that we should not expect any clean threshold  $y^M$  above which the households do not pay bribes. When we consider ability and moral cost heterogeneity across different households, the relation between income and probability to pay bribes will become even smoother. Another reason for the relation between income and probability of paying bribes to be relatively smooth (rather than a step function) is that the bargaining power of the teacher is likely to vary from village to village. The following proposition summarizes the above discussion.

**Proposition 2:**

*Assume that the poorest households have no bargaining power, but bargaining power increases with income, and the richest can punish the corrupt teacher with certainty. Consider the set of households with a child in school. The probability that a household had to pay bribes for admission is a negative function of income if the bargaining power effect of income is strong enough.*

Proof: Omitted. See the online appendix.

**(4) Empirical Strategy**

For the empirical model, it is useful to decompose the bargaining power of a household into two components: a component correlated with income (denoted as  $\sigma_i^y$ ) and a second part orthogonal to income (denoted as  $\sigma_i^\psi$ ). Thus when income is included as a regressor, it also captures the effects of  $\sigma_i^y$  which we call the bargaining power effect of income in the conceptual framework. We use the following triangular empirical model of the relationship between household income and the propensity to pay a bribe by household  $i$ :

$$\begin{aligned} P(B_i = 1) &= \beta_0 + \beta_1 y_i + \pi X_i + \beta_A A_i + \beta_M M_i + \beta_\psi \sigma_i^\psi + \zeta_i \\ &= \beta_0 + \beta_1 y_i + \pi X_i + \varepsilon_i \text{ where } \varepsilon_i = \beta_A A_i + \beta_M M_i + \beta_\psi \sigma_i^\psi + \zeta_i \end{aligned} \quad (5)$$

$$\begin{aligned} y_i &= \alpha_0 + \Pi X_i + \alpha_A A_i^f + \alpha_M M_i + \alpha_1 \sigma_i^y + \varsigma_i \\ &= \alpha_0 + \Pi X_i + v_i \text{ where } v_i = \alpha_A A_i^f + \alpha_M M_i + \alpha_1 \sigma_i^y + \varsigma_i \end{aligned} \quad (6)$$

where  $y_i$  is the income,  $X_i$  is a vector of control variables and  $\varepsilon_i$  and  $v_i$  are the error terms. The assumptions regarding the components of the bargaining power imply that  $\beta_\psi < 0$ , and  $\alpha_1 > 0$ .

The amount of bribe paid is modeled as:

$$\begin{aligned} Z_i^B &= \theta_0 + \theta_1 y_i + \Gamma X_i + \theta_A A_i + \theta_M M_i + \nu_i \\ &= \theta_0 + \theta_1 y_i + \Gamma X_i + \eta_i \text{ where } \eta_i = \theta_A A_i + \theta_M M_i + \nu_i \end{aligned} \quad (7)$$

Where  $Z_i^B$  denotes amount of bribe paid by household  $i$ , and  $\eta_i$  is the error term.

Note that even though we do not observe  $\sigma_i^\psi$ , it does not cause any bias in estimating the effects of income on the probability of bribes, because it is uncorrelated with income. Assuming

that ability and morality are not correlated, the endogeneity due to omitted heterogeneity in the propensity to pay bribe equation arises because

$$Cov(\varepsilon_i, v_i) = \alpha_A \beta_A Cov(A_i, A_i^f) + \alpha_M \beta_M \sigma_M^2 > 0 \quad (8)$$

The last inequality follows from the fact that  $Cov(A_i, A_i^f) > 0$  due to genetic transmission of ability from parents to children, and  $\alpha_A, \beta_A > 0$ ,  $\alpha_M, \beta_M < 0$ . The available evidence from behavioral genetics shows that the correlation in the IQ of parents and children is about 0.50. See, for example, Plomin et al. (2008). This positive bias in the estimated effects can easily mask a negative effect of income that arises from better bargaining power of richer households. The results reported below seem to justify this worry; without credible identification, one is likely to underestimate the regressive effect of corruption and may even find spurious progressive effect.

We focus on household income as the indicator of a household's economic status. An alternative is to use household consumption expenditure which is widely used in the existing studies, motivated by the observation that consumption is usually less subject to measurement error compared to income (see Deaton (1997)). However, an important problem with consumption expenditure as an indicator of economic status in our application is that consumption and bribe payments to teachers are simultaneously determined, given income (see equations (1) and (3) above). Simultaneity bias is a serious problem in addition to omitted heterogeneity and measurement error in the case of household consumption expenditure. We thus prefer income as the indicator of the economic status of a household.

If measurement error were the only source of bias, then one could utilize some indicators of household's wealth such as housing characteristics as instruments for income under the assumption that measurement error in wealth is not correlated with the measurement error in income (Hunt and Lazslo (2012)). However, if preference and ability heterogeneity is important, then such instruments fail to satisfy the exclusion restrictions. Instead of relying on wealth indicators as instruments, we propose an alternative instrumentation strategy that exploits rainfall differences across villages as a source of exogeneous variation.

Bangladesh is a deltaic plain at the confluence of the Ganges (Padma), Brahmaputra (Jamuna), and Meghna Rivers and their tributaries. Most of the country is low lying with an

average elevation less than 10 meters above the sea level. The average annual rainfall in our sample of villages is 1598 mm, compared to 1083 mm in India and 494 mm in Pakistan. Heavy rainfall during monsoon is an important and recurrent negative shock in rural Bangladesh. To capture the negative shock due to heavy rainfall we define a dummy that takes the value of unity if the average rainfall over last 10 years in a village exceeded the 75th percentile of average rainfall for the country. This can also be thought of as a ‘flood prone areas’ dummy. We thus expect the dummy to have a negative effect on household income in the first stage regression.<sup>19</sup> One might wonder whether rainfall itself rather than the dummy for heavy rainfall would be a better instrument. Our choice is motivated by two considerations: strength of the instrument and the monotonicity condition of Imbens and Angrist (1994). First, while the response of income to a relatively large weather shock such as flooding is expected to be strong, the income response to small or marginal rainfall variation may be insignificant. That weak instrument is potentially a serious problem when rainfall is used for identification has been noted previously in the literature (see, for example, Tanboon (2005)).<sup>20</sup> Second, as discussed by Imbens and Angrist (1994), a binary instrument necessarily satisfies the monotonicity condition (their condition 3(i)) required for the validity of the LATE theorem. This is especially important in the context of the relationship between income and rainfall, which can plausibly be non-monotonic (inverted U), as too much (flood) and too little (drought) rain can reduce income substantially.

#### **(4.1) The Identifying Assumption, Potential Objections and A Falsification Test**

The main identifying assumption for the IV estimates is that heavy rainfall reduces income substantially, but is not correlated with a household’s attitude towards paying bribes, children’s genetically inherited scholastic ability, or with the measurement error in the reported income. This seems eminently plausible. To the best of our knowledge, there are no reasonable theoretical or empirical reasons to expect that the level of rainfall affects a household head’s corruptibility, a

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<sup>19</sup>It is important to appreciate that the effects of rainfall on income may vary from country to country. In a semi-arid country, more rainfall is expected to have a positive effect on income, because drought is the predominant form of negative weather shock in this context. See, for example, the recent literature on the effects of negative income shock due to droughts in Sub Saharan Africa (Miguel et al. (2004), Bruckner and Ciccone (2011), among others). In contrast, in a country such as Bangladesh where flood is the dominant type of negative weather shock, heavy rainfall is expected to have a negative effect.

<sup>20</sup>Ciccone (2011) underscores the importance of using rainfall in levels as instrument rather than year to year changes, as the interpretation of the yearly changes may be difficult because of mean-reversion.

child's ability genetically transmitted from parents, or the measurement error in reported income that results from human fallibility.

Note also that it is very unlikely that there are any significant systematic errors in reporting corruption in schools by households, because the households have little incentive to misreport; people in Bangladesh do not worry about being prosecuted for paying bribes to teachers or health providers.<sup>21</sup> The NHSC surveys administered by Transparency International Bangladesh (TIB) also ensure that the respondents remain anonymous.

We discuss a number of potential objections to our identification below and provide evidence in support for our identification assumption (for an extended discussion on each potential objections, please see the working paper version of this paper, Emran et al. (2013)). The NHSC 2010 survey used for the analysis of corruption contains only limited information on household characteristics. We take advantage of a nationally representative household survey (Household Income and Expenditure Survey, HIES 2010, conducted by Bangladesh Bureau of Statistics) for the same year as the NHSC survey (2010) to provide supplementary evidence. We also provide evidence from a falsification exercise.

#### *Effects of Rainfall on Wages*

It is certainly plausible that heavy rainfall may affect the wage rate negatively, and one might wonder whether the estimated *income effect* from the IV regressions partly reflect *substitution effect* of lower wages for child labor in heavy rain areas. It is, however, important to appreciate that the focus of our study is on who pays bribes and how much among the households with children in school (recall that about 50 percent of the households with children in school do not pay bribes). Thus the fact that lower child wage might affect the cost-benefit of going to school is not relevant for our analysis where the children are in school at the time of the survey. Also, the available evidence shows that the net effect of a negative weather shock is to *increase* child labor, implying either an insignificant substitution effect, or a low substitution effect swamped by a strong income effect (see, for example, Hyder et al. (2012), Beegle et al. (2006)). To assuage any lingering doubts, we report IV estimates that control for agricultural wages and prices (spatial cost of living index) in section (8) below.

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<sup>21</sup>All three authors grew up in Bangladesh and have continuous involvement there. From their experience, it seems that people do not hesitate at all to reveal when they fall victim to corruption.

### *Rainfall and Migration*

Male migration due to heavy rainfall and the possibility of weak bargaining power of the women headed households is potentially relevant for the validity of our main conclusions. We provide evidence on the proportion of female headed households, proportion of women in the population in both the heavy rainfall and other areas to see if there are any significant differences. The evidence is reported in Table 1; there is no significant difference across the heavy rainfall and other areas in the proportion of female headed households, or male-female balance in the population (see first two rows in Table 1). Table 1 also reports the incidence of migration in response to shocks in both areas, and again there is no statistically significant difference between the heavy rainfall and other areas (see row 3 in Table 1). Thus any worry that our results can reflect male migration in response to shocks seems unfounded.

### *Damage to School Infrastructure and supplies, Demand for Local Resources, and Teachers' Income*

A potential problem with the exclusion restriction on heavy rainfall is that the school infrastructure and supplies may be destroyed or damaged by heavy rainfall (flood), and this may spur the teachers to demand money and resources from the parents. For a number of reasons discussed in details below, this concern is, however, not valid in our context. First, the school financing arrangement is very different in rural Bangladesh compared to the case in a country such as USA. Unlike in USA where local taxes are the main source of financing for public schools in a county, in Bangladesh the local financing plays very little (if any) role; even the so-called private schools are primarily financed by the central government. If a school is damaged by heavy rainfall, in all likelihood it is the government or some NGOs that come up with the required resources come forward to help.<sup>22</sup> Second, we provide direct evidence that contradicts a higher demand for resources by schools in heavy rainfall areas. If the teachers 'ask' for money from parents to cover losses due to flood, that will be reflected in 'payments without receipt' by the households in our data. It is reassuring that there is no significant difference in propensity to 'pay without receipt' across heavy rainfall and other areas (see row 8 from top in Table 1). One might worry that even though the propensity to pay is similar, the households in heavy rainfall areas are asked to pay

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<sup>22</sup>The NGOs are financed by donor money.

larger amount. Interestingly, the evidence in Panel A of Table 1 (see row 9 from top) is exactly the opposite: the households in heavy rainfall areas pay on average 182 Taka as payment without receipt, while, the households in other areas pay 271 Taka.

A related question that may come to a reader's mind at this point is whether it is likely that the heavy rainfall affects the income of the teachers negatively, and thus they ask for more bribes. Note, however, that the teacher salary is paid by the central government according to a national pay scale that does not vary by geographic location. This is true even for the teachers in the so-called private schools (although the number of private schools is much smaller in rural areas), thus their income is immune to rainfall differences or other weather shocks across regions. This implies that they are more likely to help smooth the consumption of the farmers in the village, rather than demanding money from poor households hit with a negative weather shock.

#### *Risk Averseness and Bad Health*

One might also worry that the households that live in heavy rain areas may suffer from bad health, and may be less risk averse. Evidence in Table 1 using two health indicators (chronic illness and 'sick or injured' in last thirty days) clearly shows that there is no significant differences between heavy rainfall and other areas (see rows 4 and 5 in Table 1). It is, however, important to appreciate that even if there were negative health effects of heavy rainfall, it would in no way constitute a rejection of our conclusions. Because bad health *lowers* the demand for schooling, and thus *reduces* the propensity to pay bribes, opposite to what we find from both the OLS and IV regressions reported later.

A less risk averse person is more likely to migrate, but there is no evidence that migration propensities are significantly higher in heavy rainfall areas. We provide additional evidence on this issue by looking at precautionary grain stocks and land rental.<sup>23</sup> The evidence in row 6 of Table 1 shows that grain stocks due to precautionary motive are not different in heavy rainfall areas. The evidence in Table 1 also shows that there is no significant difference in the incidence of land rental in heavy rainfall and other areas.

Note also that similar to the point made above regarding bad health, even if the households in the heavy rainfall (flood-prone) areas were less risk averse, it would not constitute an argu-

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<sup>23</sup>A household's grain stocks would primarily be determined by its land and household size. To get a reasonable estimate of precautionary grain stocks, we thus need to partial out the effects of operated land and household size.

ment against our main findings. According to the standard bargaining models, a less risk averse household would be less likely to pay bribes, and would pay *lower* bribes conditional on bribing. Our empirical results later contradict both of these implications: the households in heavy rainfall areas are not less likely to pay bribes, or they do not pay lower bribes.

### *Rainfall and Psychology of Corruption*

In an interesting analysis of the effects of poverty on crime in 19th century Bavaria, Germany, Mehlum et al. (2006) use rainfall as an instrument for the price of Rye. They point out that a potential objection to the exclusion restriction imposed on rainfall is that it may affect the ‘mood’ of a prospective criminal and thus can exert a direct effect on their outcome variable, violent crime. A similar direct effect of rainfall on the propensity to bribe for education seems less plausible. But to be as clinical as possible, we exclude contemporaneous rainfall, i.e., the year of the NHSC survey 2010, and use the average rainfall over the period 2000-2009.

### *Institutions and Rainfall*

With respect to potential differences in institutions between heavy rainfall and other areas, note that the relevant institutions we are interested in are those that deal with law and order. While historical rainfall differences across different countries may have affected settler mortality through disease environment and thus institutional development, a point emphasized by Acemoglu et al. (2001), it is difficult to see how it can be relevant for variations within a given country. Also, we use region fixed effects, so the rainfall variations within a region are used for identification. This implies that if there are any regional differences in institutions of law and order, they are mopped up by the fixed effects.

### Validity of the Identification: A Falsification Test

Here we present evidence from a falsification exercise that builds on the observation that rainfall should not affect income significantly in large cities because they do not rely on agricultural activities. This is similar to the falsification test used by Bruckner and Ciccone (2011) in their analysis of window of opportunity for democratic change. In our case, if rainfall does not affect income, and the identifying assumption that rainfall affects bribes only through income is valid, then if we regress propensity to pay bribes and the amount of bribes on the rainfall based in-

strument directly in a sample of households living in the large cities, the instrument should not have any significant effect. There are 842 households in the NHSC 2010 survey in large cities ('metropolitan cities'), out of which 753 availed educational services, and 246 paid bribes. When we regress the amount of bribes paid on the heavy rainfall dummy and a constant, the coefficient is 0.078 with a 't' statistic equal to 0.35 (column (3) in the lower panel of Table 1). Both the coefficient and the 't' statistic are barely affected if we control for income (see column (4) in the lower panel of Table 1). However, one may be concerned that the statistical insignificance of the heavy rainfall dummy in this case may be due largely to the small sample size (246 observations). We thus rely on the results for propensity to pay bribes where the sample size is more than three times as large (753 observations) for more credible evidence regarding the effects of heavy rainfall dummy on corruption in the large cities. The results are presented in columns (1) (without income as a control) and (2) (with income as a control) of the lower panel of Table 1. The evidence is clear and convincing. The heavy rainfall dummy does not have any statistically significant effect on the probability of paying bribes in the case of households that live in large cities; the 't' statistic is 0.18 in both the specifications. This provides strong evidence in favor of our identification scheme. Also, note that the inclusion of income does not affect the coefficient of heavy rainfall in any of the regressions, which suggests that heavy rainfall does not affect income significantly. This is confirmed by the results on income in the last column of the lower panel in Table 1; the 't' statistic for the coefficient on heavy rainfall is 0.92 (P value 0.36).

#### **(4.2) Heterogeneous Effects of Heavy Rainfall and Interactions Based Instruments**

As noted in the introduction, we provide additional evidence by using the interactions of heavy rainfall dummy with household characteristics as identifying instruments. The interactions as instruments exploit possible heterogeneity across households in the effects of heavy rainfall. For example, we expect that heavy rainfall (and flood) will have stronger effects on the income of those households who rely more on agriculture, such as farming households and agricultural wage laborers (unskilled labor). Thus an obvious way to introduce household heterogeneity is to interact the land owned by a household with the heavy rainfall dummy. However, there are two objections to this. First, to ensure that the exclusion restriction imposed is reasonable, we need to control for direct effects of land (possibly nonlinear), which would nullify a large part of the

income effect we are trying to capture using rainfall variations for identification. Second, the land administration is one of the more corrupt government agencies in Bangladesh, and the observed land ownership may partly be outcome of corruption. We thus use other indicators of household heterogeneity such as the age of the household head and religion. Both of these characteristics are clearly exogeneous in the context of Bangladesh, as religion is not a choice (determined at birth) for most people, because conversion is rare. The effects of rainfall on income may vary with the age of the household head, because a household with older head is more likely to be in agricultural occupation and thus be more exposed to rainfall shocks. On the other hand, a household headed by younger individual will be better able to withstand a negative shock such as flood; a young individual has more energy, and is more likely to take advantage of temporary migration to nearby town in response to a negative rainfall shock. Thus we would expect heavy rainfall to have stronger negative effects on the households headed by older individuals. The heterogeneity with respect to religion may be due, for example, to differences in social capital and strength of informal risk sharing. The minority groups usually cultivate more cohesive social network, and thus are likely to have better informal risk-sharing. Also, for historical reasons, the minority groups such as Hindu's in Bangladesh are more likely to be traders and artisans, and rely less on agriculture compared to Muslims.<sup>24</sup> However, an obvious objection to such interaction based instruments is that age and religious affiliation may have direct effect on the propensity to pay bribes. We thus follow Carneiro et al. (forthcoming) who also use similar interactions based IV strategy, and control for the possible direct effect of Muslim dummy and age of the household head (cubic polynomial terms) in the IV regressions.

## (5) Data

The main data used in this paper comes from two sources: National Household Survey on Corruption (NHSC, 2010) conducted by the Transparency International of Bangladesh (TIB) and Bandyopadhyay and Skoufias (2012) for rainfall data. As noted above, we also use HIES (2010) data for providing supplementary evidence on the validity of our identification scheme. A brief discussion of the HIES (2010) data is provided in online appendix to this paper.

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<sup>24</sup>In our data set, Muslim households own more lands on average and also more likely to be farmers and unskilled laborers.

### **(5.1) NHSC (2010)**

The data on corruption and bribe payments in acquiring educational services come from the National Household Survey on Corruption 2010 (NHSC, 2010). Using the Integrated Multipurpose Sampling (IMPS) Frame developed by the Bangladesh Bureau of Statistics as the sample frame, the survey selected 300 primary sampling units (PSUs) from 16 strata. The IMPS identified 1000 PSUs using the 2010 population census as the frame. The PSU borders are defined to be contiguous census enumeration blocks (usually about 2 blocks) and consists of 200 households. Note that with 200 households a PSU would be a small geographic unit in the context of Bangladesh where population density is very high. According to 2011 population census (preliminary report), per square kilometer population in Bangladesh is 964. The average household size in our sample is 5.84, which would imply that a PSU covers somewhat larger area than one square km. Thus PSU can be treated as a small village in most of the cases.

From each PSU, 20 households were selected randomly, giving us a total sample of 6,000 households. The sample used in our empirical study is however smaller (3760). Because we restrict the sample to those households who reported using educational services during the survey year to make sure that the households that face a zero probability of paying bribes for education are excluded. This reduces the sample size to 4876. Since incomes of households in metropolitan city corporations are not likely to be affected significantly by rainfall, we drop 851 households living in metropolitan areas. We also drop 257 households who reported having no school age children (age 6-20 years) and 2 households that failed to report the gender of the household head. Our final sample thus consists of 3,760 households. Note that since we include 20 years old in the sample, it is in principle possible to have 14 years of schooling, assuming a child enters first grade at age 6. However, it is very unlikely that the maximum is more than 12 years (Higher Secondary School Certificate), because many children start school later, it is common to enter first grade at 7/8 years of age in the rural areas. According to the Education Watch household survey 2005, about 25 percent of the children aged 11-15 were still in primary schools in rural Bangladesh.

The NHSC 2010 collected detailed information on many different types of services usage, and corruption faced by households in obtaining those services. In the case of education, an adult member of the household was asked detailed questions about facing bribery regarding different

educational services. The bribe questions were organized in four main categories: bribe payment for (i) admission into school, (ii) receiving free books, (iii) receiving scholarships, and finally (iv) implicit bribe payment in the form of paying fees or donations without receipts. Using responses to these questions, we define an overall propensity to pay bribes for education services as a dummy which takes a value of unity if household reported to pay any of these four types of explicit or implicit bribe and zero otherwise. Since paying without receipts is common in Bangladesh, and many people may not view it as paying bribes, we define an alternative propensity to pay bribe variable by excluding ‘paying without receipt’ as a bribe category. We also make a distinction between bribe paid for admission and all other types of bribe. Appendix Table A1 reports the summary statistics for different bribes related to education (please see online appendix). About 49 percent of the households reported to have paid bribe including payments made without receipts. Among the sub-categories, bribe for school admission is reported by 11 percent, for free books by 6 percent and for drawing scholarship money by 4 percent of the households. All together 18 percent of the households paid bribe for admission, free books and scholarships. About 40 percent of the households reported making a payment without receipts. In the empirical analysis we present results on both the overall propensity to pay bribe (including payment without receipts) and the sub-categories as well. As to be expected, the sample used for the analysis of the intensive margin (i.e., the amount of bribes paid) are smaller, about 1832 households, because about half of the households with children in school do not pay bribes. The amount of bribe paid includes payments made for any of the four different categories of bribe defined above. Among the households who reported positive amount of bribe payment, on average a household paid about Taka 241 during the survey year. To get a better sense of the financial burden imposed on the poor, it is instructive to look at the average bribe paid as a proportion of the household savings. The average bribes paid in schools is 9 percent of average annual household savings, while for the first and second quintile it amounts to 61 percent and 27 percent of annual household savings respectively. Bribes paid for schooling of the children can thus be a substantial burden on the poorest households.

The NHSC 2010 collected information on household size and composition, household head’s education and employment. We use this information to define control variables for our regression analysis. The survey also collected information about household’s total monthly income and

expenditure. Summary statistics for all of these variables are provided in the online appendix Table A1.

## **(5.2) Rainfall Data**

In order to define our identifying instrument, we need rainfall information which are not collected in the NHSC survey. The rainfall data are drawn from Bandyopadhyay and Skoufias (2012). The original data on rainfall come from the Climate Research Unit (CRU) of the University of East Anglia. The CRU reported estimated monthly rainfall for most of the world by the half degree resolution from 1902 to 2009. The CRU estimation combines weather station data with other information to arrive at the estimates.<sup>25</sup> To estimate the thana level rainfall from the CRU data, Bandyopadhyay and Skoufias (2012) uses area weighted averages.<sup>26</sup> To define our instruments, we use average rainfall during the 2000-2009 period. As noted before, we do not include contemporaneous rainfall (2010) to avoid any potential direct effect through factors such as mood of people. As a robustness check, we also use average rainfall over 1999-2005 period as the identifying instrument.

## **(6) Preliminary Evidence**

We begin with preliminary evidence on the extent and pattern of bribery in schools. The first interesting thing to note is that the average per capita income of the bribe payers (Tk. 1930 per month) is much lower compared to the average per capita income of non-payers (Tk. 2560 per month). This indicates that on an average the households that end up paying bribes for their children's education are relatively poorer. To explore further the basic correlations in the data, we report a series of OLS regressions with alternative controls.

As households living in a village face similar choice in terms of school access and quality, we cluster standard error at the PSU level. This is also motivated by the fact that the first stage of stratified random sampling used in NHSC 2010 selected 300 PSUs from the IMPS sample frame of

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<sup>25</sup>Previous versions of the CRU data were homogenized to reduce variability and provide more accurate estimation of mean rain at the cost of variability estimation. The version 3.1 data is not homogenized and thus allows for better variability estimates. Also, the estimates of rainfall near international boundaries are not less reliable as compared with those in the interior of the country, as the CRU estimation utilizes data from all the weather stations in the region.

<sup>26</sup>For example if an Upazila/thana covers two half degree grid cells for which CRU has rainfall estimates, then upzila/thana rainfall is estimated as the average rainfall of the two grid-cells, where the weights are the proportion of the area of the upazila/thana in each grid-cell. For details, please see Bandyopadhyay and Skoufias(2012).

1000 PSUs, as discussed above in the data section. All standard errors reported in this paper are clustered at PSU level if not reported otherwise.<sup>27</sup> All regressions also include regional dummies (six regions called ‘divisions’) to account for any spatial differences.<sup>28</sup>

### (6.1) Propensity to Pay Bribes: OLS Results

The first four columns in Table 2 provide OLS estimates of the coefficients of per capita income in the regressions of propensity to pay bribes. The Probit estimates are similar to those reported in Table 2, and thus omitted for brevity. The results reported in column (1) are from a simple bivariate specification where propensity to pay bribe is regressed on per capita household income alone. The specification in column (2) controls for household head’s age, gender and religion (a dummy if head is muslim). We also include household size and number of school-age children as additional controls as these variables may affect a household’s need and ability to pay bribes. The OLS estimates in columns (1) and (2) indicate a negative and statistically significant effect of per capita household income.

The results in the next column of Table 2 (i.e., column (3)) shows the estimate when we add PSU fixed effect to specification in column (2). The PSU fixed effect controls for spatial heterogeneity in endowment (such as soil quality), variations in prices and wages, and also heterogeneity across schools.<sup>29</sup> The estimates indicate a statistically significant and negative effect of income, although the magnitude is smaller.

Column 4 adds household head’s education and occupation to the specification in column (2). Since education and occupation are highly correlated with income, they are not ideal control variables when the interest is to estimate the *total* effects of income. They, however, may be proxies for ability and preference heterogeneity. The results in column (4) shows a smaller effect of income compared to column (2), but the conclusion that higher income deters bribe demands, or allows you to refuse to pay bribes, remain intact. The preliminary OLS regressions thus suggest

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<sup>27</sup>As discussed before, PSU is a geographic unit approximately equal to a one square Km in our data set. All the conclusions in this paper remain valid if we cluster the standard errors at the Thana level which is a somewhat larger geographic unit than the PSU.

<sup>28</sup>Note that although Rangpur became the 7th division at the beginning of 2010, the NHSC 2010 data are organized based on the six divisions before 2010.

<sup>29</sup>In rural Bangladesh, it is extremely unlikely, if not impossible, to have more than one schools in a PSU (approximately one square Km area on an average). Thus PSU fixed effect can alternatively be interpreted as school fixed effect.

strongly that bribery is regressive at the extensive margin. But as discussed above, the OLS estimate may underestimate the regressive effect of bribes, if ability and moral cost heterogeneity are important across households.

### **(6.2) Amount of Bribe Payment: OLS Results**

Conditional on paying bribes, do richer households pay higher amount of bribes? To analyze this question, we start again with a simple specification where amount of bribe paid by a household is regressed on per capita household income after controlling for time-invariant regional differences. The results reported in column (5) of Table 2 shows a statistically significant and positive effect of income on the amount of bribe paid. The next specification controls for household head's age, gender, religion and household size and number of school age children. Addition of these household level controls however leaves the magnitude and significance of income coefficient unchanged. A potential worry here is that the higher bribe payment by the rich could partly be due to the fact that they are paying for better school quality, assuming that the school quality is better in richer villages. If higher bribes are paid for better school quality, then the inclusion of PSU fixed effects should lead to a *reduction* in the magnitude of the income coefficient. Column (7) reports the results from the OLS regression with PSU fixed effects. The coefficient of income (0.077) in column (7) is nearly indistinguishable from that in column (6) (0.079). This evidence suggests that bribe is paid not for better schooling quality. The evidence that the school quality may not vary significantly across PSUs may be somewhat surprising to a reader familiar with the close connection between school quality and local income observed in many developed countries. But the close connection in the case of developed countries is driven by the fact that local taxes finance the schools. There is no reason to expect such a relation in the context of rural Bangladesh where most of the schools are public and operate without any local financing.<sup>30</sup> Column (8) controls for education and occupation of household head, consistent with expectations, the effect of income on bribe payments is a bit smaller, but remains statistically significant at the 1 percent level.

The positive coefficient of income in the amount of bribe regression suggests the presence of price discrimination in setting the bribe rate, bribes thus seem to be 'weakly progressive' at the

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<sup>30</sup>Even the private schools are largely financed by government funds in rural Bangladesh or financed primarily by NGOs and direct donor funds. See the online appendix to this paper for a description of the primary (grades 1-5) and secondary (grades 6-10) education in Bangladesh.

intensive margin.

## **(7) Estimates from an Instrumental Variables Approach**

### **(7.1) Propensity to Pay Bribes: IV Estimates**

The IV estimates for propensity to pay bribes for education services in schools are reported in Table 3 and 4. Table 3 reports the results for the case when the dependent variable is a dummy that takes on a value of 1 if a household pays bribes for admission into school or any other education services, with or without receipt. Table 4 reports disaggregate results for three different cases: (i) bribe for admission, (ii) bribe as payments without receipts, and (iii) bribes for admission, stipends etc. combined together (excluding payments without receipt).

In the first stage regressions corresponding to different specifications in Table 3, the coefficient of flood-prone area dummy is statistically significant at the 1 percent level and has the expected negative sign. Columns (1)-(4) in Table 3 report the 2SLS estimates for propensity to pay bribes where the instrument is the dummy for heavy rainfall. Column (5) reports the 2SLS estimates using interactions based instruments discussed in section (4.2) above.

Column (1) reports a specification with the set of controls similar to that in column (2) of Table 2. The first stage regression corresponding to specification (1) in Table 3 yields a coefficient of -0.64 for the heavy rainfall dummy which is significant at the 1 percent level. The Angrist-Pischke F-statistics for exclusion of the rainfall dummy is 9.72 which is larger than the Stock-Yogo critical value for 10 percent maximum relative bias (9.08). The instrument (heavy rainfall dummy) thus shows excellent strength in explaining the variations in household income. The estimated effect of income on propensity to bribe has a negative sign and is large in magnitude (-0.153). It is also statistically significant with a p-value equal to 0.02. Note that the coefficient of income in the IV regression is larger in magnitude than that in the OLS regression (column (2), Table 2). This is consistent with the conjecture that the OLS coefficient is biased toward zero (or positive) due to measurement error and positive selection on unobserved ability and moral cost heterogeneity.

The estimation results in column (1) are from a linear probability model. Since our dependent variable is binary, we also report estimates from the conditional maximum likelihood estimation (CMLE) method suggested by Rivers and Voung (1988) that includes the estimated residual from the first stage as a control function term. The marginal effects (evaluated at the mean) from the

CMLE are reported in column (2) of Table 3. The CMLE estimate of the marginal effect is negative and statistically significant (p-value = 0.026). The first-stage residual term is also statistically significant at the 10 percent level confirming the importance of the endogeneity problem in the simple OLS/probit estimates. The absolute magnitude of the marginal effect of income is slightly larger (-0.168) in CMLE estimate compared with that from the linear probability model. As the estimate from the linear probability model is comparable to the CMLE estimate (marginal effect), we present results from linear probability model in rest of the paper (the CMLE estimates for other specifications are available from the authors).

The specifications in columns (1) and (2) include a number of household level controls but education or occupation of household head are omitted. The reason behind this omission is that education and occupation are important determinants of income, and thus they may capture part of the income effect on bribing propensity when included as additional controls along with income. These variables may on the other hand proxy for ability and preference regarding children's education and corruption. In the next regression (column 3), we include two dummies: an education dummy indicating if a household head has higher secondary (12 grade) or more schooling, and also an occupation dummy indicating head's employment in professional jobs (e.g. doctor, engineer, large business establishments etc). The IV results in column (3) again confirm a statistically significant (at the 5 percent) negative effect of income on propensity to pay bribe. Interestingly the estimate of coefficient of income in column (3) is almost the same as the estimates in columns (1) and (2).

The income variable used so far in specifications (1-3) is per capita income which is a good indicator of the economic status of a household. One might wonder if our results are robust to alternative definition of the income variable. It is common in applied work to use log of total household income as an indicator of a household's economic status. The last column in Table 3 reports the estimated effect of log of total income on the probability of paying bribes for education services. The estimated coefficient is negative and large in magnitude (-0.50). It is also statistically significant at the 5 percent level (P-value 0.02).

The last column in Table (3) reports the estimate from 2SLS where the interactions of the heavy rainfall dummy with age and religion of the household head are the identifying instruments,

and the specification is same as in column (1) of Table 3. As noted before, we control for the religion dummy and cubic polynomial terms of head’s age to control for any possible direct effects on the propensity to pay bribes.<sup>31</sup> Using interactions of both religion and age as instruments increases the set of households whose income can be affected by the identification scheme, and the results thus have more external validity. To improve the power of the instrument and efficiency of the 2SLS estimate, we follow the approach developed by Rajan and Subrahmanian (2008) and predict household income from a “zero stage” regression where the interactions of rainfall with household head’s age and religion are included as regressors in addition to the other controls used in the main specification (column (1) Table 3). The predicted income from the “zero stage” then is used as the identifying instrument in 2SLS regression. The estimated effect of household income from this exercise is a bit larger in magnitude compared to that reported in column (1) of Table (3).<sup>32</sup>

The results in Table (3) thus provide robust evidence that the effect of higher income on the probability of paying bribes for education of children is negative, thus confirming the conjecture that in villages the rich wield significant power and they are not likely to be subject to the bribe demands from school teachers.

## **(7.2) Propensity to Pay Bribes: Disaggregated IV Results**

The dependent variable in Table (3) measures the propensity to pay bribes for any type of education services including admission, stipend (scholarship) and free books. In this broad definition, payments without receipt for unspecified educational services is also considered a form of bribe paying, because such payments may go to teacher’s pocket. But some might argue that paying without receipt may be a particularly noisy measure of corruption. We repeat our empirical analysis where different types of bribe payments are disaggregated, and the results are reported

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<sup>31</sup>In a similar interaction based identification scheme, Carneiro et al. (forthcoming) use cubic polynomial terms to control for direct effects. We also note here that the results do not depend on the exact form of polynomial function of age, or on the inclusion of interaction of religion dummy with other exogeneous household characteristics as additional controls.

<sup>32</sup>Note that if we use only one interaction instrument at a time, the power of the instrument suffers, but the estimates of the income effect are very similar to the ones reported in columns (1) and (5) in Table (3). Also, even though we have two interaction instruments, we do not report Hansen’s J statistics in Table (3), as the effects of income may vary for different subgroups affected by different instrument, and thus heterogeneity may lead to a “rejection” of the null hypothesis. To satisfy curiosity of a reader, we note that Hansen’s J test cannot reject the null of “valid” exclusion restriction.

in Table (4).

For each category of bribes, the first column reports the 2SLS estimate based on the heavy rainfall dummy as the identifying instrument, and the second reports the corresponding estimates from interaction based instruments. Columns (1) and (2) in Table (4) reports the results from IV estimation when propensity to pay bribe for school admission is considered only. The dependent variable in columns (3) and (4) is defined to include bribe payments for all different types of educational transactions except for payments without receipts. It thus includes bribe payment for admission and for receiving scholarship money and (supposedly) free books. The dependent variable in columns (5) and (6) is propensity to pay fees without receipts. The results in Table 4 show strong evidence that income has a negative and statistically significant effect on propensity to pay bribe in two of the three categories, payments without receipts being the exception. The coefficient of income in the case of paying without receipt is not robust; it is not significant at the 10 percent level when we rely on the heavy rainfall dummy for identification, but it is significant when the interactions based instruments are used. The income effect is negative but smaller in magnitude (about one third smaller than the other bribe categories). Our results thus suggest that the main effect of income on propensity to pay bribes comes from bribe payment particularly for admission into schools, getting scholarship money and ‘free’ books.

### **(7.3) Amount of Bribe Payment: IV Estimates**

The IV results for the effects of income on the amount of bribes paid are reported in Table 5. We provide estimates both with and without correction for selection into paying bribes. The upper panel in Table 5 reports the conditional estimates without selection correction, and the bottom panel the estimates that correct for selection into paying bribes.

We begin the discussion of the results with the conditional estimates in the upper panel of Table 5. These estimates are important, because they are the appropriate ones to answer the frequently asked question in news media and policy circles: among the households paying bribes, who pays more, rich or poor? For the results in first three columns in Table 5, the identifying instrument for household income is a dummy indicating areas which receive heavy rainfall. The last (fourth) column reports estimate using the interaction based instruments. The control variables in column (1) of Table 5 corresponds to that in column (1) in Table 3. The specification in column (2)

includes additional regressors indicating household head's education above secondary level and head's employment in skilled and professional occupations. Column (3) reports estimates for the case when the indicator of the economic status of a household is log of total income instead of per capita income. Although the estimates of income coefficients are negative in all of the first three regressions in Table 5, what is more striking is that none of them are statistically significant even at the 20 percent level. The numerical magnitudes are also very small. The last column reports conditional estimate using interaction based instruments and the effect of household income is again insignificant. The results thus suggest that conditional on paying bribes, the amount paid as bribes does not vary in any significant way with the income level of the households.

The unconditional estimates that correct for selection into paying bribes in the bottom panel of Table 5 are also similar; there is little or no evidence that income matters for the amount of bribes paid by a household. Since it is extremely difficult, if not impossible, to find credible exclusion restrictions for the selection equation, we take advantage of recent advances in the econometric literature that show that in the presence of heteroskedasticity, strong identification can be achieved even though there is no standard exclusion restrictions available (see, for example, Klein and Vella (2009a, 2010), Lewbel (2012), Rigobon (2003)).<sup>33</sup> As emphasized by Rigobon (2003), heteroskedasticity can be viewed as a probabilistic shifter, similar to the shifts induced by a more standard instrument satisfying exclusion restrictions. We implement the approach developed by Klein and Vella (2009) which is appropriate for a Probit model. The approach involves two-stages: (i) in the first stage, a heteroskedastic probit model is estimated for the propensity to pay bribes, and the residuals are retrieved, (ii) in the second stage, the amount of bribe equation is estimated including the residual from heteroskedastic probit as the selection correction term. The available Monte Carlo evidence shows that Klein and Vella (2009, 2010) approach works well when there is substantial heteroskedasticity in the data, as is the case in our application (see Millimet and Tchernis (forthcoming), Ebbes et al. (2009)).

A comparison of the OLS estimates in Table 2 with the IV estimates in Table 5 shows interesting differences. While the OLS results suggest a significant positive effect of income on the

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<sup>33</sup>For recent applications of heteroskedasticity based identification, see, for example, Schaffner (2002), Rigobon (2002), Rodrik and Rigobon (2005), Klein and Vella (2009b), Emran and Hou (2013), Millimet and Tchernis (forthcoming).

amount of bribe paid, we find no statistically significant effect of income on bribe amount in the IV regressions. The results thus indicate that the positive correlation between income and bribe paid in the OLS regressions is most likely driven by unobserved preference and ability heterogeneity. The direction of omitted variables bias in the amounts of bribes paid is thus same as that in the propensity to pay bribes discussed earlier. This consistency across the results enhance our confidence in the credibility of the results. The results underscore the importance of credible identification in resolving the debate about possible unequal burden of corruption on rich and poor households.

### **(8) Robustness of the IV Results**

We report additional robustness checks in this section for the IV results. We use the heavy rainfall dummy as the identifying instrument. The results from using interaction of heavy rainfall with household head's age and religion as instruments are similar and thus are omitted for the sake of brevity alone.

#### *Alternative Sets of Controls*

The IV results reported in Tables (3)-(5) are based on two sets of control variables. Here we report IV results for three more specifications with alternative sets of control variables. The first specification reports estimates from a bare bone specification that includes only the regional fixed effect and no household or individual level controls. As can be seen from columns (1) and (2) of Table 6, the estimated effects of income on propensity to pay bribe and on the amount of bribes remain essentially unchanged when compared to the main results reported in Table (3) and (5). The next two columns of Table 6 report results from a specification that adds age, sex and religion of the household head as additional covariates; the results remain robust.

The third specification deals with the possibility that the potential negative effects of heavy rainfall (and flood) on wages may induce substitution effects. We report IV estimates that control for agricultural wages and spatial cost of living index (using our main IV, the heavy rainfall dummy based on the period 2000-2009). The results are reported in columns (5) and (6) in Table 6. They confirm the argument that the potential negative effects on wages and prices are not relevant for our results.

### *Alternative Time Period for the Rainfall Instrument*

The heavy rainfall dummy we so far used for identification is defined on the basis of 10 years data on average rainfall for the period 2000-2009. If our estimates are in fact the effects of ‘economic status’ (i.e, permanent income) of a household on bribing in schools, then the estimates should not change significantly if we use average rainfall data from a somewhat different period. We checked the sensitivity of the estimates for alternative periods, and it is reassuring that the estimates remain robust. For example, consider the estimates using rainfall data for 1999-2005 presented in columns (7) and (8) in Table 6, they are almost identical to the estimates we found earlier using the 2000-2009 rainfall data.

### **(9) Discussion and Interpretation of the IV Results**

It is now widely appreciated that, when the monotonicity condition is satisfied, the IV estimates provide us with Local Average Treatment Effect (LATE), i.e., they provide estimates of the average causal effect for those households which are affected by the instrument (i.e., the ‘compliers’). Since we exploit variations in the rainfall for our identification, our estimates are most relevant for those households whose income primarily depends on the agricultural sector. However, note that flood in a village not only affects the agricultural sector, it also affects the income in the rural non-farm sector adversely, as the demand for non-farm products goes down. The IV estimates are thus likely to be relevant for the vast majority of the households in the villages and small towns in Bangladesh.

A related important point is that our estimates pertain to a household’s long-term income (economic status), because we use ten year average rainfall data, thus the short-run rainfall variations are not used for identification here. The results remain robust when we use alternative time periods for rainfall data, such as 1999-2005.

Note that a strict interpretation of the empirical results according to the model developed in the conceptual framework section implies that the negative coefficient on income at the extensive margin captures the cases where the teacher does not *ask* for bribes, but it does not reflect the cases where the household *refuses* after facing a bribe demand. This is because the refusal depends on part of the bargaining power that is uncorrelated with income. However, the income information available to the teacher in many cases may be less precise than the income estimate

we have from the household survey. Thus the estimated effect is likely to reflect, at least partly, the ‘refusal power’ of the households after the bribe demand is made.

Another issue relevant for the interpretation of the evidence reported in this paper is that the magnitudes of the income coefficients in the IV estimates for the propensity to bribe vary significantly depending on the definition of the income variable. A reader might thus be unsure about the relevant magnitudes. To standardize the estimated effects, we use the estimates from Tables (3) and (5) to produce elasticity estimates. When income variable is defined as per capita household income, the elasticity estimate implies that a one percent increase in income reduces the propensity to pay bribe by -0.73 percent. The corresponding elasticity estimate from the specification with log of total household income is larger: -1.06. The effects of income on propensity to pay bribe is thus substantial. The difference in the elasticity estimates between per capita income and log of total income reflects the fact that the household size increases with the income in the data.

## Conclusions

We exploit the negative effects of heavy rainfall on rural economy in Bangladesh for identification of the effects of the household income on the propensities to bribe for education services, and on the amounts paid as bribes. The IV estimates provide strong evidence that income has a substantial negative effect on the probability that a household pays bribe for its children’s education; a one percent lower household income *increases* the probability that parents need to pay bribes to teachers by 1.06 percent. This evidence is consistent with an interpretation that the poor faces a higher probability of bribe demand and they cannot refuse to pay because of their weak bargaining power, while the rich, given their strong bargaining power, may not need to bribe for the schooling of their children. We find no statistically significant effect of income on the amount of bribe paid, implying that bribes are also regressive at the intensive margin: the poor pay more as a share of their income. As noted before, bribes impose a significant financial burden on the poor; as a share of household savings the average bribe payment in our data set is 61 percent for households in the poorest quintile of the income distribution.

The theoretical framework developed for the empirical analysis shows that the conditions required for bribes paid by households to be progressive are strong, especially in a typical developing

country where legal and enforcement institutions are weak, and law is enforced selectively in favor of rich and powerful. The evidence that bribery in schools is regressive both at the extensive and intensive margins is germane to the debate on the increasing inequality and a lack of economic mobility in developing countries. The recent evidence shows that intergenerational persistence in schooling, a standard measure of immobility in education, does not show any improvements in a large number of developing countries over the last few decades (Hertz et al. (2007), Emran and Shilpi (2012), Azam and Bhatt (2012)). In fact, in the case of Bangladesh, Hertz et al. (2007) find that intergenerational educational mobility has worsened over the years. This widening inequality may seem difficult to reconcile with the standard theory developed by Becker and Tomes (1979) and Solon (2004), according to which interventions such as free schooling should improve educational mobility and reduce inequality. Our analysis points to corruption in schools as a potentially important factor behind the persistence of educational immobility and inequality. Even though schooling is supposed to be free (or highly subsidized) for the poor to make the ‘playing field’ level, the evidence presented in this paper suggests that the burden of bribery in schools falls disproportionately on the poor households, and skews the ‘playing field’ against them.

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**Table 1: Evidence on the Validity of the Identification  
 Potential Differences Between Heavy Rainfall and Other Areas**

	Heavy Rainfall		Difference	t-stat	p-value
	No	Yes			
<b>Migration</b>					
Share of female in household	0.487	0.480	-0.007	1.110	0.270
Head is female	0.117	0.128	0.011	0.850	0.400
Migration in response to shocks*	0.042	0.024	-0.018	1.350	0.180
<b>Health</b>					
Chronic Illness*	0.146	0.149	0.003	0.680	0.500
Sick/injured during last 30days*	0.204	0.205	0.000	0.070	0.940
<b>Risk Aversion</b>					
Precautionary Grain Stock*	60.556	59.139	-1.417	0.060	0.950
Land rental*	0.261	0.279	0.018	0.410	0.700
<b>Payments Without Receipt</b>					
Propensity to Pay Without Receipt	0.398	0.409	-0.011	-0.62	0.540
Amount Paid Without Receipt	271	182	89	1.40	0.160
<b>Falsification Test: Effects of Heavy Rainfall on Corruption in Large Cities</b>					
	Propensity to Pay		Amount of Bribe	Income	
Heavy Rainfall Dummy ( t Statistic)	0.102 (0.18)	0.099 (0.18)	0.078 (0.35)	0.082 (0.37)	0.33 (0.92)
Income	No	Yes	No	Yes	
Number of Observations	753	753	246	246	753

Note: \*Data source is Household Income and Expenditure survey (2010)

**Table 2: Propensity to Pay Bribes: Preliminary Results (OLS)**

	Propensity to pay bribe				Amount Paid as bribe			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Per Capita Income</b>	<b>-0.043</b>	<b>-0.038</b>	<b>-0.017</b>	<b>-0.023</b>	<b>0.080</b>	<b>0.079</b>	<b>0.077</b>	<b>0.057</b>
	(9.16)***	(8.25)***	(3.51)***	(4.95)***	(2.72)***	(2.86)***	(2.72)***	(3.28)***
Household size		-0.010	-0.008	-0.006		-0.011	-0.014	-0.016
		(2.07)**	(1.96)*	(1.13)		(2.12)**	(2.59)**	(2.83)***
No. of School age children		0.057	0.050	0.048		0.006	0.024	0.010
		(6.21)***	(5.94)***	(5.35)***		(0.21)	(1.60)	(0.37)
Age of Head		-0.002	-0.003	-0.002		0.003	0.002	0.002
		(3.82)***	(4.00)***	(2.73)***		(3.05)***	(1.96)*	(2.26)**
Head Female		-0.011	0.017	-0.016		0.040	-0.008	0.044
		(0.40)	(0.65)	(0.60)		(0.93)	(0.23)	(0.97)
Head Muslim		0.016	-0.013	0.009		0.004	-0.004	0.029
		(0.48)	(0.37)	(0.26)		(0.07)	(0.10)	(0.41)
Head's education secondary or above				-0.141				0.153
				(7.13)***				(1.90)*
Head's occupation (professional=1)				-0.086				0.259
				(3.18)***				(1.02)
Regional Fixed effects	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Village Fixed effect	No	No	Yes	No	No	No	Yes	No
Observations	3760	3760	3760	3760	1832	1832	1832	1832

Notes: (1) Standard errors are clustered at the primary sampling unit (PSU) level

(2) Robust t statistics in parentheses

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 3: Effects of Household Income on the Propensity to Pay Bribe: IV estimates**

	<b>Propensity to pay</b>				
	Main Specification (1)	Conditional MLE (2)	Additional Controls (3)	Alt. Income Variable (4)	Interaction Instrument (5)
<b>Per Capita Income</b>	<b>-0.153</b>	<b>-0.168</b>	<b>-0.158</b>		<b>-0.175</b>
	(-2.34)**	(-2.30)**	(-2.09)**		(-2.85)**
<b>log(income)</b>				<b>-0.498</b> <b>(-2.28)**</b>	
Household size	-0.015 (-2.51)**	-0.017 (-2.70)***	-0.017 (-2.06)**	0.054 (1.95)*	-0.015 (-2.47)*
No. of School age children	0.016 (0.67)	0.018 (0.66)	0.019 (1.05)	0.011 (0.41)	0.006 (0.24)
Age of Head	-0.002 (1.95)*	-0.002 (1.97)**	-0.002 (2.60)***	-0.000 (0.37)	-0.015 (-0.98)
Head Female	0.027 (0.86)	0.028 (0.91)	0.025 (0.83)	-0.035 (1.03)	0.035 (1.07)
Head Muslim	0.065 (1.55)	0.068 (1.56)	0.067 (1.49)	0.080 (1.62)	0.074 (1.85)*
First Stage Residual		0.123 (1.65)*			
Head's education secondary or above			0.047 (0.44)		
Head's occupation (professional=1)			0.029 (0.38)		
Head's Age Squared					0.000 (-1.01)
Head's Age Cube					0.000 (-0.92)
<b>Sign and Significance of the Instrument in First stage</b>					
Heavy Rainfall Dummy	-0.642 (3.12)***	-0.642 (3.12)***	-0.555 (3.58)***	-0.198 (2.90)***	
Interaction Based Instrument					2.258 (3.28)***
Angist-Pischke F Statistic	9.72	9.72	12.79	8.38	10.77

Notes: (1) All regressions include regional dummies. Standard errors are clustered at the Primary Sampling Unit (PSU) level. (2) 2SLS estimates are reported except for column 2.

(3) Robust z statistics in parentheses. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

(4) Instrument for the last column is the predicted income based on household's age and religion

**Table 4: Effects of Household Income on the Propensity to Pay Different Types of Bribes**  
**IV Estimates (2SLS)**

	Propensity to pay					
	Admission		Admission and Others		Payments Without Receipt	
	(1)	(2)	(3)	(4)	(3)	(3)
<b>Per Capita Income</b>	<b>-0.145</b>	<b>-0.146</b>	<b>-0.140</b>	<b>-0.157</b>	<b>-0.090</b>	<b>-0.108</b>
	<b>(-2.62)***</b>	<b>(-2.50)***</b>	<b>(-2.47)**</b>	<b>(-2.75)***</b>	<b>(1.46)</b>	<b>(-1.82)*</b>
Individual and Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Regional Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
<b>Sign and Significance of the Instrument in First stage</b>						
Heavy Rainfall Dummy	-0.642		-0.642		-0.642	
	(3.12)***		(3.12)***		(3.12)***	
Interactions Based Instrument		2.26		2.26		2.26
		(3.28)***		(3.28)***		(3.28)***
Angrist-Pischke F Statistic	9.72	10.78	9.72	10.78	9.72	10.78

Notes: (1) Standard errors are clustered at primary sampling unit (PSU) level

(2) Robust z statistics in parentheses. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

(3) Individual and household controls Used in the Odd Numbered Columns are: Age, Gender, and Religion of Household Head, and Household Size and Number of schools age children. Even Numbered Columns also Include Household Head's Age Squared and Cubed as additional Regressors.

(4) The instrument in Even Numbered Columns is the Predicted Income from the "zero stage" using interaction of Heavy Rainfall Dummy with Household Head's Age and Religion.

**Table 5: Effects of Household Income on the Amount of Bribe Paid: IV estimates (2SLS)**

	<b>Amount of Bribe Paid</b>			
	<b>Main Specification</b>	<b>Extended Controls</b>	<b>Alt. Income Variable</b>	<b>Interaction Instrument</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
<b>Conditional on Paying Bribes</b>				
<b>Per Capita Income</b>	<b>-0.006</b>	<b>-0.063</b>		<b>-0.033</b>
	(-0.07)	(-0.64)		(-0.35)
<b>Log(Household Income)</b>			<b>-0.017</b>	
			(-0.07)	
<b>Sign and significance of the Instrument in First stage</b>				
Heavy Rainfall Dummy	-0.570	-0.450	-0.213	
	(-3.26)***	(-2.99)***	(-3.50)***	
Interactions Based Instrument				1.995
				(3.48)***
Angrist-Pischke F Statistic	10.62	8.95	12.23	12.11
<b>Estimates With Selection Correction</b>				
<b>Per Capita Income</b>	<b>-0.142</b>	<b>-0.124</b>		<b>-0.168</b>
	(-0.97)	(0.88)		(1.21)
<b>Log(Household Income)</b>			<b>-0.363</b>	
			(-0.99)	
Selection Term	-3.311	-5.03	-3.141	-6.23
	(-2.02)**	(1.27)	(-2.16)**	(-1.60)
<b>Sign and significance of the Instrument in First stage</b>				
Heavy Rainfall	-0.287	-0.295	-0.113	
	(-2.65)***	(-3.32)	(-3.05)***	
Interaction Instrument				1.14
				(3.80)***
Angrist-Pischke F Statistic	7.04	11.04	9.30	14.46

Notes: (1) All regressions include regional dummies. Standard errors are clustered at primary sampling unit level  
(2) Robust z statistics in parentheses. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 6: Robustness Checks for the IV Estimates**

	Regional Fixed Effect		Indiv. and Household Controls		IV based on 1999-2005 Rainfall		Control for Agri Wage & Spatial Price	
	Propensity to Pay (1)	Amount Paid (2)	Propensity to Pay (3)	Amount Paid (4)	Propensity to Pay (5)	Amount Paid (6)	Propensity to Pay (7)	Amount Paid (8)
<b>Per capita income</b>	<b>-0.149</b>	<b>0.003</b>	<b>-0.153</b>	<b>0.003</b>	<b>-0.153</b>	<b>-0.020</b>	<b>-0.153</b>	<b>-0.003</b>
	<b>(2.46)**</b>	<b>(0.04)</b>	<b>(2.52)**</b>	<b>(0.03)</b>	<b>(2.03)**</b>	<b>(0.21)</b>	<b>(2.33)**</b>	<b>(0.03)</b>
Indiv. and Household Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Regional Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<b>Sign and Significance of the Instrument in First stage</b>								
Heavy Rainfall Dummy	-0.707	-0.601	-0.702	-0.599	-0.564	-0.503	-0.636	-0.568
	(3.21)***	(3.40)***	(3.19)***	(3.36)***	(2.71)***	(2.90)***	(3.18)***	(3.16)***
Angrist-Pischke F Statistic	10.29	11.53	10.18	11.31	7.33	8.44	10.09	9.99
Observations	3760	1832	3760	1832	3760	1832	3718	1810

Notes: (1) All regression includes regional dummies. Standard errors are clustered at primary sampling unit (PSU) level.

(2) Indiv. and Household Controls: Household head's age, gender and religion; Household size, No. of school age children

(3) Robust z statistics in parentheses. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Not for Publication: Online Appendix to:**  
**“Admission is Free Only if Your Dad is Rich!**  
**Distributional Effects of Corruption in Schools in Developing Countries”**

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**Proof of Proposition 1**

(1.a) A teacher does not ask for bribes facing a household with income  $y_i < \tilde{y}(A_H, M_L)$  where  $\tilde{y}(A_H, M_L)$  is defined by the following equation:

$$\{1 - \tilde{\delta}\} [B^*(\tilde{y}(A_H, M_L)) + w] = w \quad (1)$$

where the maximum bribe a household  $i$  is willing to pay and still send the child to school is  $B_i^*$ , implying that at this bribe the participation constraint (3) in the main text of the paper binds. Now note that within the subset of households  $(A_H, M_L)$ , the maximum bribe that can be extracted is a negative function of income, given strict concavity of the utility function. The proof then completes by the observation that  $\tilde{y}(A_H, M_L) = \text{Min}_i(\tilde{y}(A_i, M_i))$  where  $\tilde{y}(A_i, M_i)$  is defined analogously to equation (1) above.

(1.b) A household  $i$  is willing to pay a positive amount of bribe and send the kid to school if  $u'(y_i) < q(A_i) - M_i$ . Denote the income threshold  $y^L(A_H, M_L)$  such that the following holds:  $u'(y^L(A_H, M_L)) = q(A_H) - M_L$ . So among the households with the highest ability and lowest moral cost, any household with income  $y_i < y^L(A_H, M_L)$  is unwilling to pay even an infinitesimally small positive amount of bribes. Now observe that  $q(A_H) - M_L = \text{Max}(q(A_i) - M_i)$ . Since  $u(y_i)$  is concave, this implies that  $y^L(A_H, M_L) = \text{Min}(y^L(A_i, M_i))$ .

(1.c) Consider the subset of households with a given combination of ability and moral cost  $A_i, M_i$ . So the heterogeneity in income within the group derives from endowment differences. By

implicit function theorem:

$$\frac{\partial B_i^*(A_i, M_i)}{\partial y_i} = \frac{u'(y_i - B_i) - u'(y_i)}{u'(y_i - B_i)} > 0, \forall B_i^* > 0, \text{ because } u(\cdot) \text{ is strictly concave.}$$

Since the income function implies that higher ability and lower moral cost increase income given a resource endowment  $E_i$ , the teacher can extract more bribes when facing a household with high ability and low moral cost.

(1.d) A progressive bribe function implies that the elasticity of bribe amount with respect to income is greater than 1. Thus we require:

$$\frac{\partial B_i^*}{\partial y_i} \frac{y_i}{B_i^*} > 1 \Rightarrow 1 - \frac{u'(y_i)}{u'(y_i - B_i^*)} > \frac{B_i^*}{y_i} \quad (2)$$

Because from (1.c) above we have:

$$\frac{\partial B_i^*(A_i, M_i)}{\partial y_i} = 1 - \frac{u'(y_i)}{u'(y_i - B_i^*)} \quad (3)$$

Note that the higher the second derivative of the utility function (in absolute magnitude), the more likely it is that inequality (2) above will be satisfied.

Consider the isoelastic utility function:

$$u(c) = \begin{cases} \frac{c^{1-\gamma}-1}{1-\gamma} & \text{for } \gamma > 0 \text{ and } \gamma \neq 1 \\ \log(c) & \text{for } \gamma = 1 \end{cases}$$

In this case, inequality (2) reduces to

$$1 - \left[ \frac{(y_i - B_i^*)}{y_i} \right]^\gamma > \frac{B_i^*}{y_i} \quad (4)$$

An inspection of the left hand side of inequality (4) shows that it reduces to  $\frac{B_i^*}{y_i}$  when  $\gamma = 1$ . Thus inequality (4) is violated even though utility function is concave, when  $\gamma \leq 1$ . To get a progressive bribe function, we require a utility function with stronger diminishing marginal utility than implied by the log function.

### Proof of Proposition (2)

Given the assumptions that the poorest do not have any bargaining power and the richest can punish the teacher with certainty, it follows that there exists a threshold  $y^M < \bar{y}$ , such that the following equality holds (assuming that the teacher maximizes expected income):

$$\{1 - \hat{\delta}(y^M)\} [B^*(y^M) + w] = w \quad (5)$$

It is easy to check that the expected income from bribery  $\{1 - \hat{\delta}(y)\} [B^*(y) + w]$  is a decreasing function of income if the bargaining power effect of income is strong enough in following sense:

$$\hat{\delta}'(y) > \frac{B^{*'}(y) (1 - \hat{\delta}(y))}{[B^*(y) + w]} \quad (6)$$

Thus equation (5) and inequality (6) imply together that when the bargaining effect of income is strong enough to satisfy inequality (6),  $\forall y_i > y^M$ , the following inequality holds:

$$\{1 - \hat{\delta}(y_i)\} [B^*(y_i) + w] < w \quad (7)$$

When inequality (7) is satisfied, it is optimal for the teacher not to ask for bribes facing a household with income  $y_i > y^M$ .

### Data Description: HIES 2010

The HIES is considered to be a high quality household survey implemented by Bangladesh Bureau of Statistics (BBS) with assistance from the World Bank. The survey utilizes the same three stage stratified sampling strategy to select a nationally representative sample as the NHSC. The survey selected 612 PSUs randomly. From each PSU, 20 households were selected. The total sample size is 12,240 households. We follow the same strategy to select our sample as we did in the case of NHSC 2010. We dropped households living in metropolitan areas, and households who did not have school age children or who did not have children enrolled in school. Our final sample size is 7,031 households. The total household income in NHSC 2010 is Taka 12821 which is comparable to the household income in HIES 2010: Taka 13712.

### **Primary and Secondary Education in Rural Bangladesh**

The primary schooling (grades 1-5) in rural Bangladesh is dominated by public schools, although there are also private and NGO operated schools. Almost 80 percent of enrollment are into public and registered private schools. The public schools are financed by government and a large part of the financing of the private schools also come from the government. Bangladesh Government bears the 90 percent of the salary of the teachers in registered private schools and also allocates funds for improvements and maintenance of the school infrastructure. The NGO schools provide non-formal education to the poorest section of the income distribution and are primarily located in areas not served by public or private schools.

Bangladesh enacted compulsory primary education in 1990. It established a six member 'compulsory primary education committee' in the lowest tier of local government, the union (a collection of villages). The committee was to "ensure admission and regular presence of all children of the area in primary schools" (GOB, 1990). The 1990 Act also had provisions for penalties for non-compliance. If the local committee or the parents were unable to ensure attendance of the children in the village, they could be fined up to Tk. 200. But in reality the penalty for noncompliance was not enforced. The primary schools in rural areas, public, NGO, or private, are free for every child; there is no tuition or examination fees. Government provides free books in all primary schools.

The secondary schooling (grades 6-10) infrastructure is dominated by 'private schools', public schools play a smaller role. However, most of the 'private secondary schools' (registered ones) are primarily financed by the government, including teacher salary, and capital spending, maintenance and repair of the schools. Tuition fees are charged in most of the secondary schools, but the cost of education is lower in the religious secondary schools (Education Watch, 2005). Books are freely distributed by government in all secondary schools. In January 1994, stipend was introduced for girls attending secondary schools. Under the girls' stipend program, all girls in rural areas who enter secondary school are eligible for a monthly sum ranging from 25 taka in grade 6 to 60 taka in grade 10. They also receive additional payments for new books. Three conditions need to be met for receiving stipend: (i) a minimum of 75 percent attendance rate, (ii) at least a 45 percent score in annual school exams, and (iii) staying unmarried until sitting the Secondary School Certificate or turning 18. The girls stipend program seems to have a strong effect and the girls enrollment

in secondary schools have increased substantially in recent years.

Net enrollment rates in primary schools for boys and girls were 83 percent and 81 percent in 1996, and 84 and 96 percent in 2004. Quality of education is in general low, and grade repetition and drop outs are major problems. The survival rate in primary school was 55.3 percent in 1991 and 53.5 percent in 2004, showing little improvements. The net enrollment rate in secondary schools was 38 percent for boys and 50 percent for girls in 2005 (Education Watch, 2005). There is clear evidence that poor households are at a disadvantage: the net enrollment rate in secondary schools was 25 percent for food deficit households and 59 percent for food surplus households.

*References on Education in Bangladesh*

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(2) World Bank (2008), Education for All in Bangladesh: Where Does Bangladesh Stand in Achieving the EFA Goals by 2015? Bangladesh Development Series Paper No. 24, April 2008.

(3) Education Watch (2005), The State of Secondary Education: Progress and Challenges, Dhaka, Bangladesh.

**Table A.1: Summary Statistics**

<b>Variables</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
<b>Propensity to pay bribe</b>					
All including payment w/o receipts	3760	0.49	0.50	0	1
For Admission	3760	0.11	0.31	0	1
For Scholarship payments	3760	0.04	0.20	0	1
All excluding payment w/o receipts	3760	0.18	0.39	0	1
Payment w/o receipts	3760	0.40	0.49	0	1
Amount of bribe paid annually ('000 Taka)	1832	0.24	0.98	0.01	28.48
Monthly Per Capita household income (PCI) ('000 Taka)	3760	2.26	1.94	0.2	31.83
PCI of households paying bribe ('000 Taka)	1832	1.93	1.57	0.2	16.00
PCI of households not paying bribe ('000 Taka)	1928	2.58	2.20	0.3	31.83
Log (total household income)	3760	9.21	0.67	6.91	12.21
Rainfall (mean over last 10 years) (milimetre)	3760	1598	423	1009	3299
Standard Deviation of Rainfall (mean over last 10 yr)	3760	217	63	89	552
<b>Household Characteristics</b>					
Household size	3760	5.84	2.17	2	21
No. of School age children	3760	2.11	1.06	1	7
Age of Head	3760	49.16	13.17	18	110
Head female	3760	0.12	0.32	0	1
Head Muslim	3760	0.86	0.35	0	1
Head's education secondary or above	3760	0.33	0.47	0	1
Head's occupation (professional=1)	3760	0.09	0.28	0	1

Data Source: National Household Survey on Corruption (NHSC), 2010