THREE ESSAYS ON EDUCATION OUTCOMES AND INSTITUTIONS

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by

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ABSTRACT

This dissertation, in the standard three-essay format, covers three loosely connected topics that focus on education outcomes and the quality of a country's institutions in facilitating access to sanitation in Africa.

Chapter 1 attempts to estimate peer effects on student effort. I present a structural model of friendship networks in which I introduce a student grade point average (GPA) as a positive function of the student's effort and their own characteristics. I show that my model is functionally different from the standard model as it captures heterogeneity based on whether students have friends or not. I estimate peer effects using the first wave of the National Longitudinal Study of Adolescent to Adult Health (Add Health) and by applying the generalized method of moments (GMM) approach. I find that on average, a one point increase in the mean GPA of student's peers induces the student to increase their effort that in turn increase their own GPA by 0.856 points. I also find that the estimated endogenous peer effect coefficient is significantly larger than the estimated coefficient obtained under the standard model. Furthermore, I consider an alternative specification by controlling for network endogeneity. I find that the size of the estimated peer effect does not change much. My results are robust and provide a consistent and efficient measure of peer effects, which can inform the efficiency of network-targeted public policies.

Chapter 2 examines whether expansion in institutional quality broadens access to improved sanitation in Sub-Sahara Africa. This is a published paper with two co-authors[1]. This paper employs a dynamic panel-data model and data from 44 Sub-Sahara African countries over the period 2002-2015 to estimate the direct effect of institutional quality on access to sanitation. The estimation techniques control

[1]This is a joint work with John Nana Francois and Johnson Kakeu. The paper has been published in the *Journal of Contemporary Economic Policy* in April 2021.

for potential endogeneity of regressors and country-specific effects. The results indicate that institutional quality promotes access to improved sanitation with control of corruption, regulatory quality, and voice and accountability playing the most significant roles. The results also show a dichotomy between rural and urban areas in which aspects of institutions increase access to sanitation. Specifically, in urban areas, the populace's ability to participate in selecting government and expressing freedom through associations and free media drives access to sanitation. In contrast, efficient curbing of corruption, increasing rule of law, and enhancing the capacity of governments to formulate and implement sound policies facilitate access to sanitation in rural areas. This dichotomy generates important policy implications as countries move towards achieving the Sustainable Development goal, universal access to improved sanitation.

Finally, Chapter 3 estimates partial correlation of teacher quality and language of instruction on student learning deprivation. I use a unique primary school-level dataset on standardized test scores of Senegalese and Mauritanian grade 4 students and teachers (cross-sectional data). Learning deprivation is a dichotomous variable that takes the value 1 if a student reading test score falls below the minimum reading proficiency level, and 0 if otherwise. An instrumental-variable probit model controls to some extent for the endogeneity of teacher quality due to unobserved school-specific factors correlated with both teacher quality and learning deprivation. After controlling for a range of student, socioeconomic, school, district and regional related variables, I find that a decrease of one in the average teacher test score at the school level (teacher quality) is associated with an increase of the likelihood of a student's being learning deprived by 6.05 percentage points. I also show that the learning deprivation of a student who is taught in French is 98 percentage points higher than that of a student who is taught in a familiar language, (i.e., Arabic). The results suggest that policymakers in developing countries should focus on teachers' subject knowledge in teacher recruitment, training, and compensation policies. They also shed light on the importance of using a familiar language.

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CHAPTER 1

PEER EFFECTS ON ACADEMIC ACHIEVEMENT: DO PEERS INFLUENCE STUDENT EFFORT?

1.1 Introduction

The estimation of peer effects in education has received considerable attention, especially since the publication of the Coleman (1966) report.[1] The interest in peer effects is largely policy driven as many researchers have argued that peer composition is as important a determinant of student outcomes as other widely cited inputs, including teacher quality, class size, and parental involvement (see Sacerdote, 2011; Calvo-Armengol et al., 2009; Black et al., 2013a; Burke and Sass, 2013b; Carrell et al., 2009b; Hatami et al., 2015; Boucher et al., 2022). Unlike many market-channeled effects, peer effects represent how their peers outcomes or characteristics directly influence an individuals decision or outcome. The externality of peer effects provides opportunities for policies to improve social welfare. For instance, in school financing studies (e.g., Epple and Romano (1998)), under the assumption that peers outcomes or characteristics influence educational outcomes, researchers demonstrate how an effective policy intervention that internalizes peer effects, like tuition vouchers, could

[1] The publication of the Coleman (1966) highlighted the importance of peers for students' performance, arguing that peers are more important than schools as determinants of student outcomes. Since that time, researchers have tried a variety of estimation strategies to isolate the causal effect of peers on student performance. Sacerdote (2011) and Dennis and Romano (2011) provide comprehensive reviews of the literature.

lead to a more efficient human capital investment profile. Estimating the true effect of peers on student outcomes would help inform these policies.

The estimation of peer effects on student academic achievement is a challenging task. First, existing studies generally estimate the partial correlation between the grade point average (GPA) of the student and their peers while controlling for several student characteristics (e.g., age, family background, and gender). This partial correlation is not necessarily a causal effect because students do not directly choose their GPA. Instead, they exert effort (for instance, by spending time studying outside of class) that, in turn, leads to their GPA. In addition to the student effort, the GPA depends on several other student characteristics that may be observed. Therefore, the partial correlation between the student's GPA and his friends' GPA is likely to capture other effects even when controlling for the observable student characteristics. Second, another issue is the misidentification of peer effects. There may be a correlation between a student's and his peer's GPA because both students and peers could have a high intelligence quotient (IQ). In this instance, the peer effect does not drive the correlation between the GPA. The standard linear-in means model on the GPA would "wrongly" suggest peer effect. This specific issue is different from the network endogeneity issue because the process of link formation within the network may depend on other unobservable variables other than the IQ of the students. Therefore, controlling for the network endogeneity will not address the misidentification of peer effects.

This paper confronts these conceptual and econometric problems by estimating peers' effects on student academic effort instead of GPA. I rely on a peer-effect network model where each student chooses their effort level to maximize their payoff. The level of effort, in turn, produces a GPA. The GPA is assumed to be a positive function and depends on student characteristics. Following the recent literature, (e.g., Calvo-Armengol et al., 2009), I assume that students' payoff is an additive function of a private subpayoff and a social payoff. The private subpayoff depends on the benefit related to the GPA and the cost, which is a function of the effort to achieve that GPA. The social part of the GPA describes the complementarity between the student's effort and that of their peers.

The endogenous peer effects, I estimate, are the effects on the student effort and not on the student GPA directly, as it is currently done in the literature. To my knowledge, I am the first to estimate peer effects on effort. The microeconomic model leads to a reduced-form equation different from the standard linear-in-means specification of the GPA. In fact, my model captures heterogeneity through a school fixed effect that takes two values depending on whether the students have or do not have friends. This is the main driving factor of the results of the paper which account for the larger magnitude of the endogeneous peer effect. I also control for the endogeneity of the network by using the method described in Johnsson and Moon (2021)[2] and Yan et al. (2019).

I estimate the econometric model using GMM techniques and a unique dataset on friendship networks from the National Longitudinal Study of Adolescent Health (Add Health). Add Health provides information on the characteristics and outcomes of not only the students but also their friends, making it possible to specify peer groups at the relevant level of friendship networks. My main results show that that the mean of peers GPA (and characteristics) affect student GPA and the effect for the mean of peers' GPA is consistent and larger. In particular, a change of 1.0 in the mean GPA of peers increases students' own GPA by 0.856 points. The larger magnitude for the the endogenous effect is as a result of the specification of my model which captures heterogeneity based on whether students have friends or not.

Chapter 1 is organized as follows. Section 1.2 reviews the literature on peer effects on student outcomes and existing solutions in estimating social interactions. Section

[2]This paper explains the method to correct endogeneity of the social connections using a control function approach.

1.3 presents the structural model and section 1.4 discusses the econometric model including the associated identification strategy. Section 1.5 presents the data and demonstrates the results. Section 1.6 discusses the robustness analysis conducted. Concluding remarks are provided in Section 1.7.

1.2 Related Literature

I contribute to the literature on peer effects on students outcome (e.g. Lin (2010); Sacerdote (2011); Black et al. (2013b); Burke and Sass (2013a); Carrell et al. (2009a); Zabel (2008)). These studies can be classified into two categories - standard and network framework[3]. Existing studies estimate a partial correlation between a student's educational achievement and her peers' academic achievement. Most studies found a small effect on peers. I estimate peer effects on student effort instead of academic performance, as done in most studies. This distinction is important as it deeply affects the causal interpretation of peer effects. Peer effects take a source in the unobserved individual effort. Ignoring this relationship between a student's academic performance and his effort would lead to a biased estimation of peer effects. By doing so, I show that peers have a significant and large impact on student effort.

In particular, my paper is closest to Calvo-Armengol et al. (2009), who investigate peer effects on students' school performance in social networks. The authors do not observe student effort and have assumed that can be directly substituted with the student grade point average (GPA), the measure of his school performance. Hence, they estimate peer effects as the partial correlation between a student's GPA and his peer's average GPA. Their estimation ignores that GPA could depend on unobservable characteristics (e.g., a students intellectual quotient). So even if they control for

[3]In the standard framework, individuals interact in groups, e.g., in a classroom, in a dorm, etc. Under that framework, individuals are affected by all others in their group and none outside the group. In the network framework, individuals interact within networks, and the peer group is distinct for all individuals.

observable characteristics, the partial correlation between a student's GPA and her friend's GPA will likely capture other effects besides the peer effects. My model addresses this issue by assuming that a student's GPA is linked in a linear way to her observable characteristics, her effort, and a random term. This assumption is also made in Boucher and Fortin (2016); however, the authors did not estimate the model after making this assumption. By doing so, I show that peers have a significant and large impact on student effort, which translates into higher effects on school performance.

I also contribute to the literature on peer effects in networks (see Bramoulle et al. (2020) for a recent review). My structural model is closely linked to the Bramoulle et al. (2009) model. Although identification conditions are well known, few papers study the implications of such models when assuming the relationship between student effort and school performance. I present a GMM estimation procedure and show that the identification of the model is not impaired by my assumption on the relationship between student effort and school performance.

Finally, I also contribute to recent literature discussing network endogeneity. A common source of correlation is introduced by the endogeneity of the network structure. Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016; Hsieh and Lin (2017) show that there might exist an unobservable variable, correlated with the students outcome (e.g., academic achievement), as well as with their friendship choices. Existing papers do not deny this important issue, but in practice, the computational cost is often too high to also allow for network endogeneity. This was the case for Boucher et al. (2022). Our paper deal with network endogeneity by combining methodologies discussed in Johnsson and Moon (2021) and Yan et al. (2019).

1.3 The Structural Model

Many studies identify peer effects on student academic achievement (i.e., GPA) using a reduced-form equation that indirectly assumes that students choose their GPA (e.g., Lin, 2010; Hsieh and Lin, 2017). I hypothesize that the closest story to the real world is that students choose their level of effort to exert, which yields their GPA. Since GPA is not directly transmitted from one student to another, nor can it be directly chosen by any student, peer effects will take source in the unobserved level of effort a student will choose to exert. In this section, I present a structural model that identifies peer effects on effort through students' GPA.[4]

Network

There are S schools and I denote by n_s the number of students in school s, where $s \in \{1, \dots, S\}$. Let i denote the i-th student in school s. Students in each school s interact through a directed network that can be represented by an $n_s \times n_s$-adjacency matrix $\mathbf{A}_s = [\mathbf{a}_{s,ij}]_{ij}$, where the (i, j)-th entry $\mathbf{a}_{s,ij} = 1$ if student j is $i's$ friend and $\mathbf{a}_{s,ij} = 0$, otherwise. A directed network is defined as the one that considers friendship relationships as not being reciprocal; i.e. $\mathbf{a}_{s,ij}$ is not necessarily equal to $\mathbf{a}_{s,ji}$. [5]
I also assume that $\mathbf{a}_{s,ii} = 0$ for any i in any school. This means that student i cannot interact with themselves. In addition, I only consider within-school interactions; whereby students only interact with peers from their school and have no friends in other schools. This restriction is known as maximality is also considered by Calvo-Armengol et al. (2009). Finally, I define the social interaction matrix $\mathbf{G}_s = [\mathbf{g}_{s,ij}]_{ij}$ as the row-normalized adjacent matrix $\mathbf{A}_s$; that is, $\mathbf{g}_{s,ij} = 1/n_{s,i}$ if j is i's friend and $\mathbf{g}_{s,ij} = 0$ otherwise, where $n_{s,i}$ is the number of friends student i has.

[4]This model can also be used to study peer influence on many other outcomes that depend on exerted effort. An example may be the body mass index which cannot be directly decided.

[5]The Add Health data make it possible to know who nominates whom in a network; and some relationships within the data are not reciprocal; see section 1.5.3.

For illustration purposes, I consider a school with four students (i_1, i_2, i_3, i_4) within the network. In this case, if matrix $\mathbf{A}$ is represented as follows:

$$\begin{array}{ccccc} & i_1 & i_2 & i_3 & i_4 \\ i_1 & 0 & 0 & 1 & 1 \\ i_2 & 0 & 0 & 0 & 0 \\ i_3 & 1 & 0 & 0 & 0 \\ i_4 & 1 & 1 & 1 & 0 \end{array}$$

where student i_1 nominates students i_3 and i_4 as his friends or peers, student i_2 does not nominate any friends, and so on and so forth. Then, matrix $\mathbf{G}$ takes the following form:

$$\begin{array}{ccccc} & i_1 & i_2 & i_3 & i_4 \\ i_1 & 0 & 0 & 1/2 & 1/2 \\ i_2 & 0 & 0 & 0 & 0 \\ i_3 & 1 & 0 & 0 & 0 \\ i_4 & 1/3 & 1/3 & 1/3 & 0 \end{array}$$

Preferences

Let $y_{s,i}$ be the unit of GPA achieved by student i in school s. Let equation (1.3.1) be the function representing the relationship between a student GPA, their effort, observable characteristics and a random term. This hypothesized relationship constitutes my contribution to the literature. To be precise, the relationship is as follows:

$$y_{s,i} = \alpha_s + \delta e_{s,i} + \mathbf{x}'_{s,i}\boldsymbol{\theta} + \eta_{s,i}, \tag{1.3.1}$$

where $\delta > 0$ and α_s, $\boldsymbol{\theta}$ are unknown parameters; $y_{s,i}$ is the GPA of student i in school s and $\mathbf{x}'_{s,i}$ is a K-vector of observable student characteristics such as age, gender, race, etc. $e_{s,i}$ denotes the level of effort that student i chooses to exert to achieve a GPA level; and $\eta_{s,i}$ is a random term representing their unobservable characteristics. The positive sign of δ has support in the peer effect literature as it is hypothesized that GPA is a positive function of the effort (see e.g., Michaels and Miethe (1989); Brint and Cantwell (2010); Plant et al. (2005)). I assume that a student's GPA is a linear function the student's effort for simplicity. The parameter α_s captures unobserved school heterogeneity, such as teacher quality or school management, that influences GPA.

I assume that student i preferences can be represented using a linear-quadratic utility function given by (1.3.2) as done in Calvo-Armengol et al. (2009) and Blume et al. (2015). Each student chooses their level of effort $e_{s,i}$ and obtains a payoff $u_{s,i}(e_{s,i}, \mathbf{e}_{s,-i}, y_{s,i})$ that depends on the underlying network $\mathbf{G}_s$, in the following way :

$$u_{s,i}(e_{s,i}, \mathbf{e}_{s,-i}, y_{s,i}) = \underbrace{(c_s + \mathbf{x}'_{s,i}\boldsymbol{\beta} + \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \varepsilon_{s,i})y_{s,i} - \frac{e_{s,i}^2}{2}}_{\text{private sub-utility}} + \underbrace{\lambda e_{s,i}\mathbf{g}_{s,i}\mathbf{e}_s}_{\text{social sub-utility}} , \quad (1.3.2)$$

where c_s, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ are unknown parameters. The parameter of interest is λ as it captures the endogenous peer effects. The term $\mathbf{g}_{s,i}$ denotes the i-th row of the social interaction matrix $\mathbf{G}_s$; the variable $\mathbf{X}_s = (\mathbf{x}_{s,1}, \ldots, \mathbf{x}_{s,n_s})'$ represents the vector matrix of all students observable characteristics in school s; $\mathbf{e}_s = (e_{s,1}, \ldots, e_{s,n_s})'$ is the vector of student efforts in school s and; $\mathbf{e}_{s,-i} = (e_{s,1}, \ldots, e_{s,i-1}, e_{s,i}, \ldots, e_{s,n})'$ is the vector of the efforts where $e_{s,i}$ is excluded. The term $\mathbf{g}_{s,i}\mathbf{e}_s$ represents the average peers' effort. I assume that the $\mathbf{X}_s$ is exogenous, in the sense that it is independent of $\boldsymbol{\eta}_s$ and $\boldsymbol{\varepsilon}_s = (\varepsilon_{s,1}, \ldots, \varepsilon_{s,n_s})'$ for all s.

The payoff function (1.3.2) is separable into two components: a private and a social sub-utility . The first two expressions on the right-hand side of equation (1.3.2) correspond to the private sub-utility. The third expression, which describes the social sub-utility, features social interactions. In the private sub-utility, the term $(c_s +$

$\mathbf{x}'_{s,i}\boldsymbol{\beta} + \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \varepsilon_{s,i}$) represents the benefit enjoyed per unit of GPA achieved[6]; and the other term $e_{s,i}^2/2$ is the cost borne by a student to achieve a specific GPA.

The social sub-utility, $\lambda e_{s,i}\mathbf{g}_{s,i}\mathbf{e}_s$, represents the synergy created by interacting with peers. It means that an increase in the average peer group's effort, $\mathbf{g}_{s,i}\mathbf{e}_s$, influences student i marginal utility if $\lambda \neq 0$. When $\lambda > 0$, the payoff function (1.3.2) implies complementary between student own efforts and their peers' efforts, whereas $\lambda < 0$ suggests a substitute.

Equilibrium

Next, I substitute equation (1.3.1) into equation (1.3.2) to obtain a payoff function (A-2) that does not depend on the GPA, $y_{s,i}$ but rather on effort[7]. The new payoff function characterizes a strategic game with complete information in which students simultaneously choose their effort as to maximize their payoff. Students' best response function can be expressed as

$$e_{s,i} = \delta c_s + \lambda \mathbf{g}_{s,i}\mathbf{e}_s + \delta \mathbf{x}'_{s,i}\boldsymbol{\beta} + \delta \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \delta \varepsilon_{s,i}. \tag{1.3.3}$$

Equation (1.3.3) features endogenous peer effects as a student optimal effort level is a function of the average effort of peers. The parameter λ captures *peers effects* on the effort. If $\lambda > 0$, then students' effort level increases when their peers increase their effort.

As the network matrix $\mathbf{G}_s$ is row-normalized, I show that the game has a unique Nash equilibrium (NE) if the following restriction holds.

Assumption 1.3.1. $|\lambda| < 1$

The condition $|\lambda| < 1$ set above is based on the literature (see e.g., Bramoulle et al.,

[6] As in Calvo-Armengol et al. (2009), this benefit introduces heterogeneity between students as it depends on student characteristics $\mathbf{x}_{s,i}$ and peer group average characteristics $\mathbf{g}_{s,i}\mathbf{X}_s$ called *contextual variables* (see Manski, 1993).

[7] See Appendix A.1 for a step-by-step derivation

2009). This condition is necessary so that the effort is uniquely determined from equation (1.3.3). This condition is also verified in the data section (see below section 1.5). It means that students do not increase, in absolute value, their effort greater than the increase in the effort of their peers. Put differently, when the average effort of a student's peers increases by one, the increase/decrease in the student effort is less than one.

Under Assumption 1.3.1, the NE is given by

$$\mathbf{e}_s = (\mathbf{I}_{n_s} - \lambda \mathbf{G}_s)^{-1}(\delta c_s \mathbf{1}_{n_s} + \delta \mathbf{X}_s \boldsymbol{\beta} + \delta \mathbf{G}_s \mathbf{X}_s \boldsymbol{\gamma} + \delta \boldsymbol{\varepsilon}_s), \tag{1.3.4}$$

where $\mathbf{1}_{n_s}$ is an n_s-vector of ones and $\boldsymbol{\varepsilon}_s = (\varepsilon_{s,1}, \ldots, \varepsilon_{s,n_s})'$ is a vector of random terms of each student in school s. See Appendix A.1 for the step-by-step derivation.

1.4 The Econometric Model and Identification Strategy

If student effort levels were observed, I can directly estimate the endogenous peer effect parameter (λ) from equation (1.3.3). As I do not observe the effort, equation (1.3.3) cannot be estimated directly. In this section, I derive the econometric model that is estimated. I show that the specification of my model is different from the standard model used in the literature like in Calvo-Armengol et al. (2009). This difference is as result of the relationship between GPA and effort (1.3.1) whereby I assume that students do not choose their GPA but rather their effort. My new specification raises some identification issues. I discuss parameter identification and present my estimation strategy.

1.4.1 The Econometric Model

I derive the reduced-form model by substituting equation (1.3.1) in equation (1.3.3). I obtain equation (1.4.5) which is a function of GPA instead of effort[8]:

$$y_{s,i} = \kappa_{s,i} + \lambda \mathbf{g}_{s,i}\mathbf{y}_s + \mathbf{x}'_{s,i}\tilde{\boldsymbol{\beta}} + \mathbf{g}_{s,i}\mathbf{X}_s\tilde{\boldsymbol{\gamma}} + (\boldsymbol{\omega}_{s,i} - \lambda \mathbf{g}_{s,i})\boldsymbol{\eta}_s + \delta^2 \varepsilon_{s,i}, \tag{1.4.5}$$

where:

$$\kappa_{s,i} = \delta^2 c_s + (1 - \lambda \mathbf{g}_{s,i}\mathbf{1}_{n_s})\alpha_s$$

$$\tilde{\boldsymbol{\beta}} = \delta^2 \boldsymbol{\beta} + \boldsymbol{\theta}$$

$$\tilde{\boldsymbol{\gamma}} = \delta^2 \boldsymbol{\gamma} - \lambda \boldsymbol{\theta}$$

$\boldsymbol{\omega}_{s,i}$ is a row-vector of dimension n_s in which all the elements are equal to zero, except the i-th element which is one. Appendix A.2 provides the step-by-step calculations. The reduced-form model (1.4.5) is functionally different from the reduced-form in the standard model usually found in the literature.[9] This difference stems from the fact that the literature assumes that students directly choose their GPA. Whereas, I hypothesize that students rather choose their effort and their effort will in turn lead to their GPA. My hypothesis is embedded in the linear relationship (1.3.1) presented above. Moreover, two econometric issues arise when one compares the standard model shown in Appendix A.2 to the reduced-form model shown in equation (1.4.5).

First, the intercept parameter i.e. the school fixed effect in the standard model denoted by δc_s takes a unique value for all students in the same school. However, in equation (1.4.5), the school fixed effect is $\kappa_{s,i}$ and takes two values depending on

[8]See Appendix A.2 for a step-by-step derivation

[9]The standard model reduced form is of the form: $y_{s,i} = \delta c_s + \lambda \mathbf{g}_{s,i}\mathbf{y}_s + \delta \mathbf{x}'_{s,i}\boldsymbol{\beta} + \delta \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \delta \varepsilon_{s,i}$. See Appendix A.2

whether student i has friends or not. This is shown in the equation above for $\kappa_{s,i}$. Since, the network matrix $\mathbf{G}_s$ is row-normalized, $\mathbf{g}_{s,i}\mathbf{1}_{n_s} = 0$ if i has no friends and $\mathbf{g}_{s,i}\mathbf{1}_{n_s} = 1$ otherwise. By substituting $\mathbf{g}_{s,i}\mathbf{1}_{n_s}$ by its values, the equation above for $\kappa_{s,i}$ becomes:

$$\kappa_{s,i} = \begin{cases} \bar{\kappa}_s = \delta^2 c_s + \alpha_s, & \text{if } i \text{ has no friends} \\ \hat{\kappa}_s = \delta^2 c_s + (1-\lambda)\alpha_s, & \text{otherwise} \end{cases}$$

The parameters $\hat{\kappa}_s$ and $\bar{\kappa}_s$ are school fixed effects that capture unobserved (by the modeler) variables that have common effects on the outcome of all students who have friends within the network and those who do not, respectively (e.g., same teachers, same school culture, same school facilities). Unlike in the standard model, the school fixed effect takes on two distinct values except if $\alpha_s = 0$ or $\lambda = 0$. But these conditions are not achievable for the following reasons. On one hand, with many schools s, imposing the condition that the school fixed effect $\alpha_s = 0$ from equation (1.3.1) is true for all s seems unrealistic. That is, there will be instances school fixed effects such as teacher quality, school culture cannot be ignored. On the other hand, the endogenous peer effect $\lambda = 0$ is not feasible and this will be confirmed empirically in the section below. Therefore, it is necessary to consider that there are unobserved student fixed effects $\bar{\kappa}_s$ and $\hat{\kappa}_s$ that capture heterogeneity based on whether the student has friends or not. Ignoring these unobserved factors can be viewed as a misspecification issue and leads to biased estimations of the endogenous parameter.

Some empirical studies (e.g., Lin, 2010) show that the endogenous peer effect estimate is robust when one considers the sub-sample of non-isolated students - that is, those who name a friend and are nominated by others. This evidence does not address the misspecification issue I raise above. Indeed, even with the sub-sample of non-isolated students, it is possible to have students who have no friends. Those students are still in the sub-sample because they are nominated by others. Removing them involves a missing network data issue (see Boucher and Houndetoungan, 2022).

Second, the standard model does not take into account the term $(\boldsymbol{\omega}_{s,i} - \lambda\mathbf{g}_{s,i})\boldsymbol{\eta}_s$ in the structure of the disturbance error. This term captures heterogeneity associated with unobserved attributes of the peers. For example, if $\boldsymbol{\eta}$ is IQ, then the IQ of peers can have an impact on a student. This heterogeneity is different from that of correlated effects where the error term $\eta_{s,i}$ is a linear function of the average peer error term (see Manski, 1993). Ignoring this term leads to a misspecification of the structure of the variance of the disturbance terms, which may lead to inefficient estimate of the endogenous peer effect. But, ignoring the structure of the error term does not lead to inconsistent estimations of the endogenous peer effect if $\boldsymbol{\eta}_s$ is independent of $\mathbf{G}_s$. Indeed, even in the case of correlated effects, estimating the model without controlling for the correlated effects leads to a consistent estimator (Kelejian and Prucha, 1998). This means that I can get a consistent estimator of the endogeneous peer effects by ignoring the term $(\boldsymbol{\omega}_{s,i} - \lambda\mathbf{g}_{s,i})\boldsymbol{\eta}_s$. To account for the misspecification of the variance structure of the disturbance terms, the standard errors can be estimated using a robust approach.

1.4.2 Parameter Identification Analysis

In this section, I discuss the steps taken to identify the parameters of the model given by equation (1.4.5).

Restrictions on parameters

In the first step, I set restrictions on the model (1.4.5) in order to identify the parameters of interest: the endogenous peer effect λ, the coefficient β capturing effect of student own characteristics and the contextual effect γ. These restrictions are warranted because it is not feasible to identify all the parameters of the model.

Specifically, the parameter δ cannot be identified as it enters equation (1.4.5) only through its product with c_s, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and the error term $\varepsilon_{s,i}$. The parameters $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ cannot be identified separately because they only appear in equation (1.4.5) through the term $\tilde{\boldsymbol{\gamma}} = \delta^2\boldsymbol{\gamma} - \lambda\boldsymbol{\theta}$. Even if $\tilde{\boldsymbol{\gamma}}$ is known, there are several possible values of $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ that will satisfy the condition $\tilde{\boldsymbol{\gamma}} = \delta^2\boldsymbol{\gamma} - \lambda\boldsymbol{\theta}$.

Let condition 1.4.1 be the identification restrictions:

Condition 1.4.1 (identification restrictions)**.** $\delta = 1$ *and* $\boldsymbol{\theta} = 0$.

Condition 1.4.1 does not change the econometric specification of the reduced-form model. Plugging in this condition into equation (1.4.5), I obtain the following equation (1.4.6):

$$y_{s,i} = \kappa_{s,i} + \lambda\mathbf{g}_{s,i}\mathbf{y}_s + \mathbf{x}'_{s,i}\boldsymbol{\beta} + \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + (\boldsymbol{\omega}_{s,i} - \lambda\mathbf{g}_{s,i})\boldsymbol{\eta}_s + \varepsilon_{s,i}, \tag{1.4.6}$$

where $\kappa_{s,i}$ takes on the value $\bar{\kappa}_s = c_s + \alpha_s$ for students who have no friends, and the value $\hat{\kappa}_s = c_s + (1-\lambda)\alpha_s$ if otherwise. As discussed above, the parameter $\bar{\kappa}_s$ and $\hat{\kappa}_s$ are network fixed effects in each school that capture unobserved characteristics depending on whether students have friends or not.

School-mean transformation

In the second step, I perform a school-mean transformation which expresses the model (1.4.6) in deviation from the individual student's school. This transformation is done because the the modeler cannot consistently estimate equation (1.4.6) due to the the incidental parameters problem.[10] To avoid the incidental parameters problem, the standard approach is to eliminate the school fixed effect $\kappa_{s,i}$ from equation (1.4.6) by performing a school-means or global transformation. In analogy with the within

[10] The incidental parameters problem, as it was defined by incidental, and discussed at length in Lancaster (2000a), occurs whenever the data available for each group or school are finite. That is, as the number of schools grows to infinity, $\kappa_{s,i}$ also goes to infinity.

transformation in panel data models, this can be done by taking appropriate global differences between structural equations. For that purpose, I introduce the global transformation matrix $\mathbf{J}_s$:

$$\mathbf{J}_s = \mathbf{I}_{n_s} - \frac{1}{\bar{n}_s}\bar{\boldsymbol{\ell}}_s\bar{\boldsymbol{\ell}}'_s - \frac{1}{\hat{n}_s}\hat{\boldsymbol{\ell}}_s\hat{\boldsymbol{\ell}}'_s$$

where for any given school s, $\bar{n}_s$ denotes the number of students who have no friends and $\hat{n}_s$ the number of students who have friends. For illustration purposes, assuming there are four students in the network as in section 1.3, $\mathbf{J}_s$ can be written as :

$$\mathbf{J}_s = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{I}_{n_s}} - \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{\frac{1}{\bar{n}_s}\bar{\boldsymbol{\ell}}_s\bar{\boldsymbol{\ell}}'_s} - \underbrace{\begin{bmatrix} 1/3 & 0 & 1/3 & 1/3 \\ 0 & 0 & 0 & 0 \\ 1/3 & 0 & 1/3 & 1/3 \\ 1/3 & 0 & 1/3 & 1/3 \end{bmatrix}}_{\frac{1}{\hat{n}_s}\hat{\boldsymbol{\ell}}_s\hat{\boldsymbol{\ell}}'_s}$$

with $\frac{1}{\bar{n}_s}\bar{\boldsymbol{\ell}}_s\bar{\boldsymbol{\ell}}'_s$ being the matrix that averages over all students in i's school who have no friends; and $\frac{1}{\hat{n}_s}\hat{\boldsymbol{\ell}}_s\hat{\boldsymbol{\ell}}'_s$ being the matrix that averages over all students in i's school who have friends/peers.[11] By convention, I impose that $\frac{1}{\bar{n}_s}\bar{\boldsymbol{\ell}}_s\bar{\boldsymbol{\ell}}'_s = 0$ if $\bar{n}_s = 0$ and that $\frac{1}{\hat{n}_s}\hat{\boldsymbol{\ell}}_s\hat{\boldsymbol{\ell}}'_s = 0$ if $\hat{n}_s = 0$.

Matrix $\mathbf{J}_s$ multiplies equation (1.4.6) to obtain deviation from school-means [12]. I can write equation (1.4.6) on which a within global transformation is applied as follows:

$$\mathbf{J}_s\mathbf{y}_s = \lambda\mathbf{J}_s\mathbf{G}_s\mathbf{y}_s + \mathbf{J}_s\mathbf{X}_s\boldsymbol{\beta} + \mathbf{J}_s\mathbf{G}_s\mathbf{X}_s\boldsymbol{\gamma} + \mathbf{J}_s(\mathbf{I}_{n_s} - \lambda\mathbf{G}_s)\boldsymbol{\eta}_s + \mathbf{J}_s\boldsymbol{\varepsilon}_s, \qquad (1.4.7)$$

[11] $\hat{\boldsymbol{\ell}}_s = \mathbf{G}_s\mathbf{1}_{n_s}$ and $\bar{\boldsymbol{\ell}}_s = \mathbf{1}_{n_s} - \hat{\boldsymbol{\ell}}_s$.

[12] This transformation only captures the selection bias stemming from the fact that students in the same school face a common environment. It does not address the problem of network endogeneity, which is discussed in section 1.6

By multiplying each term by $\mathbf{J}_s$, I consider equation (1.4.6) for students who have friends in deviation to the average within the subset of students who have friends in the school. Likewise, the same equation is considered for students who do not have friends in deviation to the average within the subset of student who do not have friends in the school. This within global transformation eliminates the network fixed effect $\hat{\kappa}_s$ and $\bar{\kappa}_s$ respectively. Indeed, if $\boldsymbol{\kappa}_s$ is the vector of $\kappa_{s,i}$ in the schools s, I have $\mathbf{J}_s\boldsymbol{\kappa}_s = 0$.

I rewrite equation (1.4.7) more succinctly :

$$\hat{\mathbf{y}}_s = \lambda \mathbf{G}_s \hat{\mathbf{y}}_s + \hat{\mathbf{X}}_s \boldsymbol{\beta} + \mathbf{G}_s \hat{\mathbf{X}}_s \boldsymbol{\gamma} + \hat{\boldsymbol{\upsilon}}_s, \tag{1.4.8}$$

where $\hat{\mathbf{y}}_s = \mathbf{J}_s \mathbf{y}_s$; $\hat{\mathbf{X}}_s = \mathbf{J}_s \mathbf{X}_s$; and $\hat{\boldsymbol{\upsilon}}_s = \mathbf{J}_s(\mathbf{I}_{n_s} - \lambda \mathbf{G}_s)\boldsymbol{\eta}_s + \mathbf{J}_s \boldsymbol{\varepsilon}_s$

Conditions under which the parameters of the model are identified

Exogenous Friendship networks. I discuss these identification conditions by assuming that friendship networks are exogenous.[13] An exogenous networks refers to the condition that $\mathbf{G}_s$ is independent on $\boldsymbol{\eta}_s$ and $\boldsymbol{\varepsilon}_s$. This is captured in the following assumption:

Assumption 1.4.1 (exogenous networks)**.** *The process* $(\upsilon_{s,i})'$ *is independent and centered conditionally on* $\mathbf{G}_s$ *and* $\hat{\mathbf{X}}_s$

This conditional exogeneity assumption signifies that the friendship network, represented by the social interaction matrix $\mathbf{G}_s$ is taken as exogenous relative to the GPA determination in equation 1.4.8. That is, the process by which students form friendship links is completely exogenous. Assumption 1.4.1 also imposes that the matrix of student own characteristics, $\hat{\mathbf{X}}_s$ is exogenous.

[13] Later, I discuss the case for endogenous friendship networks in section 1.6.

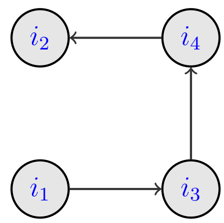
Linear independence of regressors. To identify the parameters λ, β and γ in equation (1.4.8), the regressors, i.e. the right-hand side variables need to be linearly independent just like in a simple linear model. First, the expected mean GPA of a student's peers conditional on the student's observable characteristics, $\mathbb{E}(\mathbf{G}_s\hat{\mathbf{y}}_s|\hat{\mathbf{X}}_s)$ should not be perfectly collinear with the regressors $\hat{\mathbf{X}}_s$ and $\mathbf{G}_s\hat{\mathbf{X}}_s$. Here, simultaneity in the behavior of interacting students introduces a perfect collinearity between the expected mean GPA of peers ($\mathbf{G}_s\hat{\mathbf{y}}_s$) and the mean characteristics of peers ($\mathbf{G}_s\hat{\mathbf{X}}_s$). This is what Manski (1993) refers to as the reflection problem which hinders the identification of the endogenous effect λ from the exogenous or contextual effects γ. Second, the matrices $\hat{\mathbf{X}}_s$ and $\mathbf{G}_s\hat{\mathbf{X}}_s$ should not be multi-collinear, i.e. the columns of the matrices are independent from each other. Overall, linear independence of the regressors is the necessary condition that must be satisfied to ensure that λ, β and γ are identified. To ensure that the regressors are linearly independent, I set following assumption 1.4.2:

Assumption 1.4.2. *(i) Suppose* $\lambda\boldsymbol{\beta} + \boldsymbol{\gamma} \neq 0$. *(ii) If there exist at least one school containing a pair of students separated by a link of distance three (see figure 1.4.1); and (iii) the matrices* $\hat{\mathbf{X}}_s$, $\mathbf{G}_s\hat{\mathbf{X}}_s$ *are full rank.*

Condition i means that the characteristics of peers i.e. the contextual variables has some (direct and/or indirect) effect on a student's expected GPA. The condition is satisfied as soon as β and γ have the same sign, $\lambda > 0$, and $\beta \neq 0$. With several characteristics of peers, condition i must be satisfied for at least one of them. Condition ii implies that the structure of the network matters for identification of the parameters of the model. Specifically, if there exist a pair of students in any school such that the shortest path between them is of length 3, then the parameters can be identified.

Finally, condition iii guarantees that the matrices $\hat{\mathbf{X}}_s$, $\mathbf{G}_s\hat{\mathbf{X}}_s$ are not multi-colinear.[14] In Appendix A.2, I present the proof for assumption 1.4.2.

Figure 1.4.1: Illustration of the Identification



where $\rightarrow$ means that the node on the left side is friend of the node on the right side

Conclusions for identification of parameters. Finally, I summarize under proposition 1.4.1 all the conditions and assumptions discussed above which allow to identify the parameters of the model : λ, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$.

Proposition 1.4.1. *λ, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ are identified if and only if the following are true: assumption 1.3.1; condition 1.4.1; and assumption 1.4.2.*

Assumption 1.3.1 guarantees that the model has a unique Nash Equilibrium. Condition 1.4.1 set restrictions on the structural parameters to ensure the main parameters can be estimated econometrically. Assumption 1.4.2 ensure that all the independent variables are linearly independent.

1.4.3 Estimation Strategy

I use the generalized method of moments (GMM) to estimate the model as shown in (1.4.8). This is the appropriate estimation method because the mean GPA of peers ($\mathbf{G}_s\hat{\mathbf{y}}_s$) on the right hand-side of the equation is not a truly exogenous variable. In fact, the mean GPA of peers is correlated with the error term $\hat{\upsilon}_s$; that $\mathbb{E}[(\mathbf{G}_s\hat{\mathbf{y}}_s)\hat{\upsilon}_s^{'}] \neq 0$ as a result of simultaneity bias: student i GPA depends on the mean GPA of their

[14] Assumption 1.4.2 is also considered in Bramoulle et al. (2009), however in my case I account for the fact that in the network there are both students who have friends and students who do not have friends. In this sense, conditions ii and iii are stronger that the ones set in Bramoulle et al. (2009)

peers (where j is included), and student j GPA also depends on the mean GPA of their peers (where i or a peer of i could be included). One implication of this endogeneity of the mean GPA of peers, is that the parameters λ, β and γ of equation (1.4.8) cannot be consistently estimated by ordinary least squares. However, it can be estimated with GMM techniques by finding valid instrumental variables.

The structure of the network provides a natural instrument variable (IV) for the mean GPA of peers, i.e. the characteristics of peers of peers $\mathbf{G}_s^2\hat{\mathbf{X}}_s$. This IV has been discussed extensively in the literature (see Kelejian and Prucha, 1998; Bramoulle et al., 2009). For the characteristics of peers of peers $\mathbf{G}_s^2\hat{\mathbf{X}}_s$ to be valid instruments, they need to be correlated with the mean GPA of peers ($\mathbf{G}_s\hat{\mathbf{y}}_s$) and uncorrelated with the error term, $\hat{\upsilon}_s$ in equation (1.4.8). These can be shown by considering figure 1.4.1 with four students in the network. Let's take the case of student i_1 and student i_4 to illustrate. Since student i_1 is friend with student i_3, equation (1.4.8) for student i_1 can be written as:

$$y_{s,i_1} = \lambda y_{s,i_3} + \beta x_{s,i_1} + \gamma x_{s,i_3} + \upsilon_{s,i_1} \tag{1.4.9}$$

where y_{s,i_3} is the mean GPA of the peers of student i_1, x_{s,i_3} is the mean characteristics of peers of student i_1. In this case, i_1 has only one friend/peer i.e i_3.
Doing the same for student i_3 who is friend with i_4:

$$y_{s,i_3} = \lambda y_{s,i_4} + \beta x_{s,i_3} + \gamma x_{s,i_4} + \upsilon_{s,i_3} \tag{1.4.10}$$

where y_{s,i_4} is the mean GPA of the peers of student i_3, x_{s,i_4} is the mean characteristics of peers of student i_3. In this case, i_3 has only one friend/peer i.e i_4.
In equation (1.4.3), the mean GPA of peers (y_{s,i_3}) is endogenous because it is correlated with the error term, υ_{s,i_1}. So there is a need to find an instrument for y_{s,i_3}. First, this instrument needs to be correlated with y_{s,i_3}. In equation (1.4.3), the char-

acteristics of student i_4 (who is a peer/friend of i_3), $\boldsymbol{x}_{s,i_4}$ are correlated to y_{s,i_3} and therefore satisfy this correlation requirement. Second, the instrument should be exogenous, i.e. the instrument should not be affected by other variables in student i_1 equation. This requirement is also satisfied when one considers the characteristics of student i_4 ($\boldsymbol{x}_{s,i_4}$) which is not directly correlated to y_{s,i_1} because there is no direct link between i_1 and i_4. Therefore, $\boldsymbol{x}_{s,i_4}$ is a good instrument for y_{s,i_3} in equation (1.4.3). This illustration captures the intuition that the characteristics of the peers of peers who are not direct peers may serve as instruments for the actions of a student's own peers.

Using characteristics of peers of peers as IV for the mean GPA of peers leads to consistent GMM estimators of λ, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ under Assumptions 1.3.1–1.4.2. Indeed, figure 1.4.1 shows that the presence of at least one intermediate student allows the researcher to use the characteristics of peers of peers (peers-of-peers who are not direct peers) as an instrument to account for the mean GPA of peers. I also compute robust standard errors to account for the heteroskedasticity of the error terms (e.g., see Baum et al., 2003).

1.5 Data and Main Results

1.5.1 Add Health Survey

The analysis is made possible by the use of a unique database, the National Longitudinal Study of Adolescent to Adult Health (Add Health). The Add Health survey has been designed to understand the impact of the social environment i.e., friends, family, and school) on adolescents' behavior in the United States by collecting data on students in grades 7 to 12 from a nationally representative sample of 145 middle, junior high, and high schools. These students were selected based on a stratified nationally representative sample of all public and private schools in the United States[15].

Five waves of the data are available and this paper uses the wave I survey which allow to construct the friendship networks. In wave I, a 45-minute in-school questionnaire was given to all the students attending the sampled schools from September 1994 to April 1995, resulting in a total sample of 90,118 students. The students were asked to nominate up to five male and five female friends. Friends identification numbers make it possible to link students' information to their friends and construct friendship networks. Within a school, only a students friends are identified as their peers and are given equal weight, while all the others in the same school are assigned zero weight. The other questions asked in the survey covered the students demographics, family background; grades in four subjects (English/language arts, history/social sciences, mathematics, and science), and health-related information.

1.5.2 Descriptive Statistics

For the purpose of the estimation, I retain 68,430 students from 141 schools, i.e. 76 percent of the whole sample of the Wave I survey. This final sample is constructed based on several selection criteria. First, I remove self-friendships and friendships between students from different schools, given that there are data entry errors. Second, I remove students whose identifiers are missing. Third, I remove students whose school information is missing, whose GPA is missing, and whose information on their own and their friend's characteristics are also missing. I end up with 68,430 students from 141 schools. The largest school has 2,156 students, and about 50 percent of the schools have more than 500 students. Social interactions are represented by the network matrix **G** described in section 1.3 as the row-normalized adjacency matrix. The network matrix represents directed links i.e. $\mathbf{g}_{s,ij} > 0$ if j is i's friend but not

[15]available on the website https://addhealth.cpc.unc.edu/documentation/study-design/

necessarily vice versa. In the sample, there are both students who nominated friends and who do not nominate any friends as discussed below.

Table 1.5.1 provides descriptive statistics of the estimation sample of 68,430 students and appendix A.4 provides the definitions of the variables used in this paper. The dependent variable GPA is the average grade of four subjects: mathematics, science, English or language arts, and history or social science. It is calculated based on responses obtained from students on their respective letter grades (A, B, C, D or lower) obtained in the four subjects. I re-coded these letter grades so that A=4; B=3; C=2; and D=1. The mean GPA of the sample is 2.813 out of 4, with a standard deviation of 0.806. I studied the effect of peers' behavior on student's GPA by recognizing that peers' behavior impact student's own effort.

The independent variables include the student's own characteristics ($\mathbf{X}_s$), the mean characteristics of their peers or the contextual variables ($\mathbf{G}_s\mathbf{X}_s$), and the mean GPA of their peers, i.e. ($\mathbf{G}_s\mathbf{y}_s$). For the set of student characteristics, following previous studies (e.g., Duncan et al. (2001), Lin (2010)), and given data availability, the model uses age, gender, race, years in school, club membership, family structure, mothers education, and mothers occupation. For the contextual variables, I use the same set of variables as the student characteristics, allowing any element that directly determines a students outcome also to affect their peers.

The mean age of the students is about 15 years, on average, and they have attended their current school for 2.5 years. Among the 68,430 observations, 48.7 percent are boys, 16.4 percent are Hispanic, 64.7 percent are white, and 16.8 percent are black. Asians account for 7 percent, and 9.5 percent of the sample are of other races. About 74.1 of the students live with both parents. The highest education level achieved is high school for about 30.6 percent of the student's mothers, is beyond high school for 16.9 percent of the mothers, and is less than 12 years for 41.9 percent of the mothers. As for mothers occupations, Add Health provides a detailed list with more than 15 categories. I combine these occupations into four broader categories, along with a missing indicator[16]. Specifically, 20.2 percent of the students' mothers work in professional occupations, such as teachers, doctors, lawyers, and executives. Twenty percent of the mothers are homemakers or do not work. 43.5 percent of the mothers hold other jobs.

These variables cover almost all the background information in the Add Health Survey. One limitation is that I do not have information on family income, arguably an essential determinant of students academic achievement. But the education and occupations of the mothers should provide some information about family income and thus should capture most, if not all, of the effects of family income. Conversely, school-level information, such as school quality and teacher-student ratio, is not necessary as I eliminate school fixed effects by doing a school-mean transformation using the matrix $\mathbf{J}$ as discussed in section 1.4.

Statistics about the network indicate that the average number of friends per student is 3.4 (1.6 male and 1.9 female friends). This reveals that on average, students actually report having fewer friends than the number of allowed nominations during the survey. This may suggest that the constraint put in the number of friends by the Add Health study is not binding. In addition, figure **??** shows that only 1 percent of the student population that nominated 10 friends in total. Therefore, it can be the results of the estimation will not be biased by potential top coding issues as discussed in Griffith (2022).

About 22 percent out of the 68,430 students in the sample do not have friends. That is, there are 14,900 students who did not name a friend (see figure **??** for the distribution of the number of friendships in the sample). Statistics are also reported for students that do not have friends on the 5th and 6th columns of table 1.5.1. As shown, these students tend to have a lower GPA.

[16] Lin (2010) showed that different combinations of occupations have been considered, and the estimation results are robust to these changes.

Table 1.5.1: Descriptive Statistics

Variable	Own Characteristics				Peers' Average Characteristics	
	All students		Students with no peers			
	Mean	SD	Mean	SD	Mean	SD
GPA	2.813	(0.806)	2.705	(0.834)	2.246	(1.287)
Student characteristics						
Age	15.074	(1.680)	15.364	(1.656)	11.760	(6.355)
Years in school	2.506	(1.422)	2.361	(1.351)	2.042	(1.511)
Female	0.513	(0.500)	0.418	(0.493)	0.423	(0.359)
(Male)	0.487	(0.500)	0.582	(0.493)	0.359	(0.339)
(White)	0.647	(0.478)	0.550	(0.498)	0.525	(0.449)
Black	0.168	(0.374)	0.205	(0.404)	0.126	(0.302)
Asian	0.070	(0.254)	0.085	(0.279)	0.052	(0.176)
Hispanic	0.164	(0.370)	0.228	(0.420)	0.117	(0.262)
Other race	0.095	(0.293)	0.120	(0.325)	0.067	(0.177)
Club member	0.937	(0.243)	0.877	(0.328)	0.743	(0.412)
Live with both parents	0.741	(0.438)	0.691	(0.462)	0.596	(0.398)
Mother education and job status						
Mother education less than HS	0.419	(0.493)	0.376	(0.493)	0.349	(0.345)
(Mother education HS)	0.306	(0.461)	0.282	(0.461)	0.241	(0.284)
Mother education more than HS	0.169	(0.375)	0.191	(0.393)	0.119	(0.222)
Mother education missing	0.106	(0.308)	0.151	(0.358)	0.073	(0.167)
Professional	0.202	(0.402)	0.172	(0.377)	0.173	(0.240)
(Stay home)	0.206	(0.405)	0.214	(0.410)	0.153	(0.229)
Other jobs	0.435	(0.496)	0.406	(0.491)	0.346	(0.322)
Mother job missing	0.157	(0.364)	0.208	(0.406)	0.110	(0.203)
Network statistics						
Number of friends	3.44		0.00		–	–
N= 68,430						

Notes: The variables in brackets are the omitted categories in the following estimations.

1.5.3 Main Results

Table 1.5.2 presents the GMM estimates from the peer effects model when the friendship network is exogenous. I first estimate the standard model (c.f Model 1 in table 1.5.2) found in previous studies such Calvo-Armengol et al. (2009); Lin and Lee (2010). In the standard model, the econometrician assumes that the mean GPA of peers directly influences a student's GPA. Hence, the standard model specification includes only one intercept term (i.e. school fixed effect), which is common to all students. Then, I estimate my model (c.f Model 2 in table 1.5.2) shown in equation 1.4.8, whereby peers' behavior rather influences student effort, which in turn leads to their GPA. My model specification includes two school fixed effects, capturing heterogeneity depending on whether the student has or does not have friends. I use as instruments for the mean GPA of peers, $\mathbf{G}_s\mathbf{y}_s$, all peers characteristics of the second degree, that is, the (mean) attributes of peers of peers $\mathbf{G}_s^2\mathbf{X}_s$. The weak instrument test statistic and overidentification test statistic are reported at the bottom of the table.

Results indicate that the endogenous peer effect coefficient (λ) is significant in both Model 1 and Model 2. The value of the coefficient in Model 2 (0.856) is larger by over 1.6 times the size of the coefficient of Model 1 (0.507). Using my model specification, I find a bigger and more precise endogenous peer effect estimate. The magnitude of the estimated peer effect coefficient confirm that peer effects take source in the unobserved student effort and this distinction is important as it deeply affects the causal interpretation of peer effect (Boucher and Fortin (2016). The estimated magnitude suggests that, ceteris paribus, a 1-point increase in the mean GPA of student's peers induces them to raise their effort which lead to an increase in their own GPA by 0.856 points. This finding is aligned with the empirical literature (Sacerdote (2011)) highlighting the importance of peers as determinants of student performance. I find a bigger magnitude of the peer effect because my model allows to account and differentiate between students who have friends/peers and students who do not have friends. As noted above, about 22 percent of students in the sample do not nominate any friends and they tend to have a relatively lower GPA. Failing to account for this difference, leads to a downward bias in the estimation of the endogenous peer effect coefficient.

Next, I present results for Model 2 on the students own characteristics and contextual variables. Most estimated coefficients for the students own characteristics have the expected signs. Female students score 0.165 grade points higher than male students, suggesting that girls in 1994-1995 perform better than boys. Older students tend to do worse, and students who have been in the current school for longer periods tend to do better. Black, Hispanic, and students of other races score 0.091, 0.121, and 0.026 points lower than white students, respectively, while Asian students score 0.194 points higher than white students. Students who participate in club activities and who live in with both their parents score 0.138 and 0.091 points higher, respectively. Mothers education is an important determinant of student GPA, and the relationship is positive. Specifically, children of mothers with a less than high school education score 0.068 points lower than those of high school graduate mothers, while children of mothers who have education beyond high school achieve 0.124 points higher. Compared to students whose mothers do not work, children of teachers, lawyers, or other professional job holders are more successful (at 10 percent level), while children of other job holders have lower grades.

The coefficients are significant for a number of contextual variables. In particular, my results indicate that students who have relatively more female peers tend to perform worse than students who have male peers. This result suggests that a higher fraction of girls among a student's peers could provide greater distraction for teenage boys especially considering the period 1994-1995. In fact, Coleman (1966) suggested that suggested that there may be a distraction inherent in mixed gender educational settings for adolescents. He pointed to the strong emphasis on rating and dating in American high school culture, with mixed peer groups having a negative effect on achievement of both girls and boys. Moreover, the student's GPA decreases when their peers are asians, participate in club activities, mothers job is professional. On the contrary, the student's GPA rises with the mean age of their peers, when their peers are black, and when their peers are hispanic.

At the bottom of the table, I report the results from a Wald test which rejects $\mathbf{G}_s^2\mathbf{X}_s$ as weak instruments (statistics = 67 at the 1 percent significance level). I also report a Sargan test which rejects the null hypothesis that the model is overidentified (statistics=19). Thus, I conclude that the instruments are valid and Model 2 is not overidentified.

Table 1.5.2: Exogeneous Network - Results for Peer Effects on Student Academic Achievement

Explanatory Variable	Model 1				Model 2			
	Individual effects		**Contextual effects**		**Individual effects**		**Contextual effects**	
	Coef.	SE.	Coef.	SE.	Coef.	SE.	Coef.	SE.
Endogenous peer effects (λ)	**0.507*** **	**0.029**	**-**	**-**	**0.856** **	**0.042**	**-**	**-**
Student characteristics								
Female	0.176***	0.006	-0.108*	0.012	0.165***	0.006	-0.123*	0.013
Age	-0.015**	0.003	-0.073*	0.004	-0.043**	0.004	0.024**	0.006
Years in school	0.033***	0.003	0.028***	0.004	0.027***	0.003	-0.009	0.006
Hispanic	-0.101**	0.010	0.050*	0.017	-0.091**	0.011	0.087***	0.020
Black	-0.131**	0.012	-0.007	0.016	-0.121**	0.014	0.070***	0.020
Asian	0.218***	0.013	-0.043	0.022	0.194***	0.014	-0.135***	0.026
Other race	-0.026**	0.011	-0.046**	0.020	-0.026**	0.011	-0.001	0.022
Club	0.157***	0.013	-0.142*	0.030	0.138***	0.013	-0.084**	0.029
Live with both parents	0.107***	0.007	-0.040	0.017	0.091***	0.008	-0.019	0.017
Mother education and job status								
Mother education is less than HS	-0.076**	0.009	-0.050**	0.017	-0.068**	0.009	0.025	0.019
Mother education is greater than HS	0.151***	0.007	0.027	0.017	0.124***	0.008	-0.032	0.019
Mother education missing	0.031***	0.013	-0.070*	0.025	0.026**	0.013	-0.031	0.027
Mother's job is professional	0.039***	0.009	-0.056*	0.018	0.032***	0.009	-0.034*	0.019
Mother other jobs	-0.040**	0.007	-0.105**	0.015	-0.037**	0.008	-0.022	0.016
Mother job is missing	-0.078**	0.011	-0.116**	0.022	-0.070*	0.012	0.008	0.024
Weak instruments test (Wald statistic)	112	(p-value = 0.000)			67	(p-value = 0.000)		
Overidentification test (Sargan statistic)	101	(p-value = 0.000)			19	(p-value = 0.217)		

Notes: The dependent variable is GPA. The sample size is 68,430. The estimates of the standard errors of the estimated parameters do take the presence of heteroskedasticity into account.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

1.6 Robustness Analysis

I relax the assumption on the exogeneity of the friendship network. Assuming exogeneity of the friendship network is easily sustainable when peers are randomly assigned (see Sacerdote, 2001). However, in a context where students choose their friends/peers, assuming that this decision is exogenous is quite restrictive. In everyday life students with common preferences or characteristics tend to associate together. These could be source of estimation bias when students self-select into friendship links.

In particular, endogeneity arises whenever student-level unobservables (student fixed effects) simultaneously determine friendship formation and the outcome of interest (i.e. the GPA). Such unobservables could include homophily which is a phenomenon whereby friendship links tend to form between students sharing common features such as age and sex; see, for example, McPherson et al. (2001). Other unobserved student attributes such as IQ, degree of sociability could also influence a student's decision to interact with other students in the school.

In this section, I provide evidence that the results obtained above are robust after controlling for network endogeneity. To so so, I first present the methodology used to address network endogeneity. Then, I report the results when the estimation is done using the conventional GMM approach as the one done above (c.f Model 3 in table 1.6.3) and also an optimal GMM aproach (c.f Model 4 in table 1.6.3).

1.6.1 Methodology Used to Control for Network Endogeneity

The endogeneity of the network can then be viewed as an omission of important variables in equation (1.4.8). These variables represent unobserved student fixed effects which are captured by the error terms. To address this omitted variables issue, I use an approach similar to Johnsson and Moon (2021) control function approach. The intuition of the control function approach is to correct the endogeneity of the network by including the unobserved "omitted" factors (student fixed effects) in the model as new regressors. To do so, I consider a network formation model with degree heterogeneity i.e. a network with students exhibiting different degree of interactions as in Hsieh and Lee (2016); Graham (2017); Dzemski (2019); Yan et al. (2019). The probability for student j to be friend with student i is given as:

$$P_{ij} = \mathbb{P}(a_{s,ij} = 1|\ddot{\mathbf{x}}_{s,ij}, \ddot{\boldsymbol{\beta}}, \mu_{s,i}^{in}, \mu_{s,j}^{out}) = F(\ddot{\mathbf{x}}'_{s,ij}\ddot{\boldsymbol{\beta}} + \mu_{s,i}^{in} + \mu_{s,j}^{out}), \tag{1.6.11}$$

where $\ddot{\mathbf{x}}_{s,ij}$ is a vector of observed dyad variables, i.e. is a vector of observed characteristics of the pair of students (i and j), $\ddot{\boldsymbol{\beta}}$ is an unknown parameter, $\mu_{s,i}^{in}$ and $\mu_{s,i}^{out}$ are unobserved attributes. The vector $\ddot{\mathbf{x}}_{s,ij}$ contains social distances between students i and j based on several observed characteristic such as the absolute difference of the ages ($|age_i - age_j|$), an indicator of whether i and j have the same sex, an indicator of whether both participate in club activities. The parameter $\ddot{\boldsymbol{\beta}}$ captures the influence of each social distance on the likelihood to form a social link. The unobserved attribute (student fixed effect) $\mu_{s,i}^{in}$ captures any unobserved factor that only influence the probabilities of social links going from i to other students, whereas the unobserved attribute (fixed effect) $\mu_{s,i}^{out}$ represents unobserved factors that influence the probabilities of social links going from other students to student i.
These unobserved student fixed effects $\mu_{s,i}^{in}$ and $\mu_{s,i}^{out}$ play an important role, especially in the case of directed networks. This particular specification of the unobserved attributes is also considered by Dzemski (2019) and Yan et al. (2019), and is more flexible than the specific case of Graham (2017) discussed in Johnsson and Moon (2021). By convention, I set $P_{ii} = 0$ so that i is not friend with i and $P_{ij} = 0$ if i and j are not from the same school.

The endogeneity of the network comes from the fact that μ_i^{in} and μ_i^{out} could be correlated to υ_i in equation (1.4.8). I assume that this correlation can be characterized as follows:

Assumption 1.6.1 (endogenous networks). *(i) For any s and i, $\upsilon_{s,i} = \beta^{in}\mu^{in}_{s,i} + \beta^{out}\mu^{out}_{s,i} + \upsilon^*_{s,i}$ where β^{in} and β^{out} are unknown parameters; (ii) The process $(\upsilon^*_{s,i})'$ is independent and centered conditionally on $\mathbf{G}_s$ and $\mathbf{X}_s$.*

Assuming that $\upsilon_{s,i}$ is additively separated in μ^{in}_j, μ^{out}_j, and the new error term $\upsilon^*_{s,i}$ simplifies the model. This restriction is also considered by Hsieh and Lee (2016); Goldsmith-Pinkham and Imbens (2013). However, it is stronger than that the control function assumption considered by Johnsson and Moon (2021). The control function approach assumes that the error term is additively separated in some unknown function of the unobserved attributes and a new error term. Given the structure of the error term in my model, assuming an unknown function as in Johnsson and Moon (2021) makes the model complicated to deal with econometrically.

The key feature of assumption 1.6.1 is that $\mathbf{G}_s$ and $\mathbf{X}_s$ are exogenous with respect to the new error term $\upsilon^*_{s,i}$. Let $\boldsymbol{\mu^{in}_s} = (\mu^{in}_{s,1}, \dots, \mu^{in}_{s,n_s})'$, $\boldsymbol{\mu^{out}_s} = (\mu^{out}_{s,1}, \dots, \mu^{out}_{s,n_s})'$ be the vectors of unobserved attributes in the school s. Let also $\boldsymbol{\upsilon}^*_s = (\upsilon^*_{s,1}, \dots, \upsilon^*_{s,n_s})'$ be the vector of the new error term. By replacing $\boldsymbol{\upsilon_s}$ by $\beta^{in}\boldsymbol{\mu^{in}_s} + \beta^{out}\boldsymbol{\mu^{out}_s} + \boldsymbol{\upsilon}^*_s$ in equation (1.4.8), I have:

$$\hat{\mathbf{y}}_s = \lambda \mathbf{G}_s \hat{\mathbf{y}}_s + \hat{\mathbf{X}}_s \boldsymbol{\beta} + \mathbf{G}_s \hat{\mathbf{X}}_s + \hat{\boldsymbol{\chi}}_s \boldsymbol{\psi} + \boldsymbol{\upsilon}^*_s, \tag{1.6.12}$$

where $\hat{\boldsymbol{\chi}}_s = \mathbf{J}_s \boldsymbol{\chi}_s = [\boldsymbol{\mu^{in}_s},\ \boldsymbol{\mu^{out}_s},\ \mathbf{G}_s\boldsymbol{\mu^{in}_s},\ \mathbf{G}_s\boldsymbol{\mu^{out}_s}]$ and $\boldsymbol{\psi} = (\beta^{in}; \beta^{out}; -\lambda\beta^{in}; -\lambda\beta^{out})'$. The new equation is essentially equation (1.4.8) with additional explanatory variables $\boldsymbol{\mu^{in}_s}$, $\boldsymbol{\mu^{out}_s}$, $\mathbf{G}_s\boldsymbol{\mu^{in}_s}$, and $\mathbf{G}_s\boldsymbol{\mu^{out}_s}$. All parameters of this model are identified under under condition 1.4.1 and assumptions 1.3.1–1.4.2 discussed above.

I estimate equation (1.6.12) using GMM techniques given that the mean GPA of peers is endogenous. My estimation strategy is done in two stages. First, I estimate $\boldsymbol{\mu^{in}_s}$ and $\boldsymbol{\mu^{out}_s}$ from equation (1.6.11) using a logit model as in Yan et al. (2019). This logit estimation raises the incidental parameter problem because the number of unobserved student attributes to be estimated increases with the sample size. Nonetheless, Yan et al. (2019) show that the estimated unobserved attributes $\boldsymbol{\mu_s^{in}}$ and $\boldsymbol{\mu_s^{out}}$ are consistent. Second, I replace $\boldsymbol{\mu_s^{in}}$ and $\boldsymbol{\mu_s^{out}}$ in equation (1.6.12) by their estimated values obtained after running the logit regression. Then, I estimate the model (i.e. equation (1.6.12)) using the GMM estimation method at this second stage. Specifically, I run both the conventional GMM as done in the case of the exogenous model described in section 1.4 and an optimal GMM as described in Kelejian and Prucha (1998) and Lee (2003). Under the conventional GMM, the characteristics of peers of peers $\mathbf{G}_s^2\mathbf{X}_s$ are used as instruments for the endogenous variable $\mathbf{G}_s\mathbf{y}_s$, i.e. the mean of peers GPA. Whereas, in the case of an optimal GMM, $\mathbb{E}\left(\mathbf{G}_s\mathbf{y}_s\right)$ are used as instruments. This optimal GMM procedure is implemented in three steps. In the first step, the conventional GMM is estimated, then I estimate the expected value of the endogenous variable ($\mathbb{E}\left(\mathbf{G}_s\mathbf{y}_s\right)$) by using the estimated parameters from the conventional GMM as a second step. In the third step, $\mathbb{E}\left(\mathbf{G}_s\mathbf{y}_s\right)$ is used as instruments for $\mathbf{G}_s\mathbf{y}_s$ and the model parameters are estimated using a GMM approach. This procedure yields an optimal GMM estimator.

1.6.2 Results

Table 1.6.3 presents the results obtained after controlling for network endogeneity. I discuss the results for both models 3 and 4. In model 3, I estimate the parameters of equation 1.6.12 using the conventional GMM approach similar to the one described in section 1.4 while in model 4 I use an optimal GMM procedure as summarized above. I report the results of the estimated unobserved student attributes (student fixed effects) and their peers/friend's mean unobserved attributes in the fifth row of the table. I also provide the Wald and Sargan statistics.

A careful comparison between model 2 (exogeneous network) and models 3 and 4 (endogeneous network) reveals that the endogenous peer effect estimate is robust to this specification which controls for network endogeneity. The estimated coefficients on student characteristics and contextual variables are also robust. As mentioned in the introduction, our paper is the first to estimate peer effects on student academic achievement after controlling for network endogeneity.

As in the case of the exogenous model, the endogenous peer effect estimate is positive and highly significant. The point estimate (0.839) is slightly lower to the point estimate obtained above for model 2 (0.856), which represents the effect of the mean GPA of peers on a students GPA through their effort. As for the student characteristics and contextual variables, the estimated coefficients do not exhibit great change after introducing and controlling for network endogeneity. For instance, female students score 0.168 grade points higher than male students, which is slightly higher than the coefficient estimated under model 2 (0.165). Moreover, as it was in model 2, students who have relatively more female peers tend to perform worse than students who have male peers. The difference in the values of the coefficient is also small; -0.123 under model 2 and -0.122 under model 3.

The results also indicate that the estimated μ^{out} and μ^{in} are statistically significant and of the expected signs. The findings suggest that unobserved student attributes both outgoing and incoming are found to positively influence the probability of forming friendship links and student GPA. Finally, as in the case of model 2, the results from a Wald test rejects $\mathbf{G}_s^2\mathbf{X}_s$ as weak instruments (statistics = 57 at the 1 percent significance level), suggesting that the intruments used are valid. The Sargan test also rejects the null hypothesis that the model is overidentified (statistics=16), suggesting that model 3 is not overidentified.

Table 1.6.3: Endogenous Network - Results for Peer Effects on Student Academic Achievement

Explanatory Variable	Model 3				Model 4			
	Individual effects		**Contextual effects**		**Individual effects**		**Contextual effects**	
	Coef.	SE.	Coef.	SE.	Coef.	SE.	Coef.	SE.
Endogeneous peer effects (λ)	**0.839****	**0.042**			**0.788*****	**0.043**		
Student characteristics								
Female	0.168***	0.006	-0.122***	0.014	0.168***	0.006	-0.115***	0.014
Age	-0.043***	0.004	0.025***	0.006	-0.043***	0.004	0.023***	0.006
Years in school	0.025***	0.003	-0.008	0.006	0.025***	0.003	-0.006	0.006
Hispanic	-0.092***	0.011	0.084***	0.020	-0.093***	0.011	0.075***	0.020
Black	-0.108***	0.014	0.070***	0.020	-0.109***	0.014	0.064**	0.020
Asian	0.193***	0.014	-0.129***	0.026	0.195***	0.014	-0.114***	0.026
Other race	-0.030**	0.011	-0.001	0.022	-0.031**	0.011	-0.003	0.022
Club	0.132***	0.013	-0.091***	0.030	0.134***	0.013	-0.074**	0.029
Live with both parents	0.090***	0.008	-0.016	0.017	0.092***	0.008	-0.008	0.017
Mother education and job status								
Mother education is less than HS	-0.066***	0.009	0.024	0.019	-0.066***	0.009	0.019	0.019
Mother education is greater than HS	0.127***	0.008	-0.029	0.020	0.131***	0.008	-0.014	0.020
Mother education missing	0.027***	0.013	-0.028	0.027	0.028*	0.013	-0.025	0.026
Mother's job is professional	0.031***	0.009	-0.034*	0.019	0.032***	0.009	-0.030	0.019
Mother other jobs	-0.038***	0.008	-0.024	0.016	-0.039***	0.008	-0.028	0.016
Mother job is missing	-0.071***	0.012	0.008	0.024	-0.072***	0.011	0.002	0.024
Unobserved attributes								
μ^{out}	0.005***	0.014			0.005***	0.001		
μ^{in}	0.014***	0.006			0.015***	0.004		
$\bar{\mu}^{out}$	-0.005	0.006			-0.001	0.008		
$\bar{\mu}^{in}$	0.003	0.020			0.003*	0.002		
Weak instruments test (Wald statistic)	57	(p-value =0.000)			51	(p-value =0.000)		
Overidentification test (Sargan statistic)	16	(p-value =0.532)			9	(p-value =0.930)		

Notes: The dependent variable is GPA. The sample size is 68,430. The estimates of the standard errors of the estimated parameters do take the presence of heteroskedasticity into account.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

1.7 Conclusion

In this paper, I study peer effects on students effort through their academic achievement, that is, their GPA. To do so, I specify a structural model where the students choose their level of effort, which in turn implies their GPA. I derive a reduced-form equation that is functionally different from the standard model. A major difference worth highlighting is that my model captures heterogeneity through a school fixed effect that takes two values depending on whether the students have or do not have friends. This heterogeneity is addressed by doing a school-mean transformation in order to yield consistent estimates. I find larger effects of the mean GPA of peers on students' own GPA. A change of 1.0 in the mean GPA of peers increases students' own GPA by 0.856 points. Given that the standard model does not take this heterogeneity into account, my model provides a more precise and consistent estimates of the endogenous peer effect.

I also consider an alternative specification. I relax the assumption of exogeneity of the network and estimate the model while considering that the friendship network is endogenous. Then, I use both the conventional GMM and the optimal GMM techniques to estimate the model. The endogenous peer effect estimate does not change much, suggesting that the main results of the model are robust to an alternative specification.

In conclusion, my paper is a first step towards estimating the true magnitude of peer effects on student outcomes such as academic achievement. There are important research avenues worth considering. One could simulate the impact of a policy change on network formation to compare outcomes between students who have friends versus students who do not have friends. Another area for further research lies in estimating a more efficient peer effect coefficient by exploring robust approaches to account for the misspecification of the variance structure of the disturbance terms.

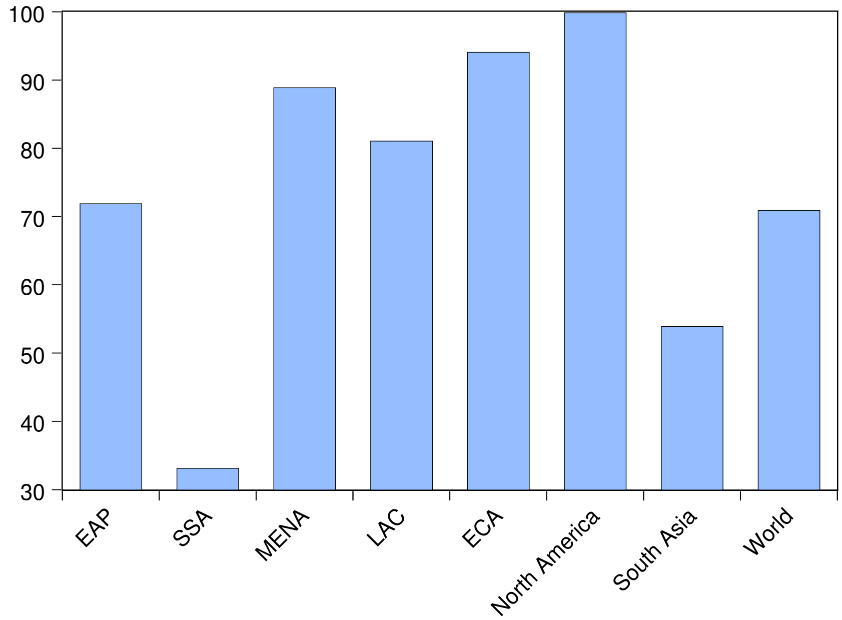
CHAPTER 2

DO BETTER INSTITUTIONS BROADEN ACCESS TO SANITATION IN SUB-SAHARA AFRICA?

2.1 Introduction

Inadequate access to safe sanitation raises the risk factors for infectious diseases and mortality. It is therefore not surprising that one of the 17 goals of the 2030 Agenda for Sustainable Development is to ensure universal access to sanitation. In 2015, 6.6 billion people (over 90 percent of world's population) used improved drinking water sources and over two thirds of the world's population (i.e., 4.9 billion people) accessed improved sanitation facilities (United Nations, 2017). While there has been progress in providing access to improved drinking water, clearly, further strides must be taken to ensure universal access to sanitation. Importantly, the 2017 United Nation progress report on the Sustainable Development Goals reveals that the lack of sanitation and its associated risks disproportionately affect sub-Sahara Africa (SSA).

Figure 2.1.1: Access to Improved Sanitation by Region (Average from 2002-2015)



Notes: Access to improved sanitation is measured by the percentage of the population with access and using improved sanitation facilities. EAP is East Asia & Pacific; MENA is Middle East and North Africa; LAC is Latin America and the Caribbeans and ECA is Europe and Central Asia.

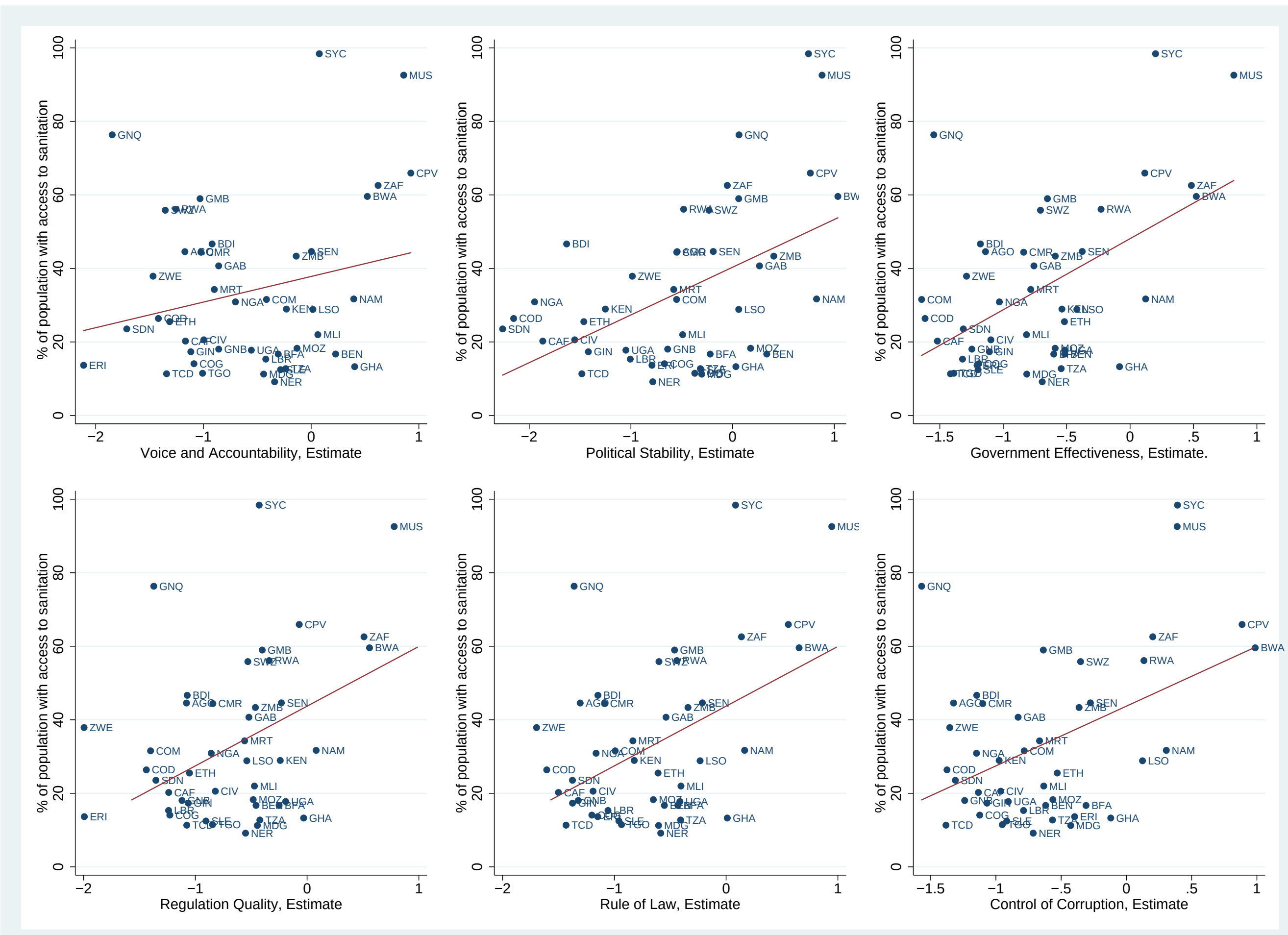
Figure 2.1.1 further elucidates the previous point by comparing the average percentage of population with access to improved sanitation across regions over the period 2002-2015. Notice that this period was characterized by the Millennium Development goals. However, as illustrated by the figure, while 71 percent of the world's population used improved sanitation facilities, only 33 percent of the population in SSA used improved sanitation. This is about 20 percentage points less than the percentage of the people who used improved sanitation in South Asia. These numbers are particularly striking as SSA is the only region where less than 50 percent of its population used improved sanitation. This gap suggests an immediate need to understand the factors that drive access to sanitation in SSA. Additionally, people without access to improved sanitation facilities live predominantly in rural areas. Consequently, to achieve universal access to basic sanitation, as well as, ending unsafe practice of open defecation requires an understanding of the determinants that drive progress in rural areas.

Institutional quality may play a crucial and direct role in broadening access to improved sanitation facilities in SSA. More precisely, effective sanitation management; hence, access to improved sanitation relies on the participation and interplay of local communities, individuals, and governmental institutions (see for instance, McGranahan, 2015). This implies that better institutions should facilitate how these stakeholders work together to facilitate access to improved sanitation. In this paper, we investigate the direct effect of institutions on access to sanitation by answering the following questions: Do better institutions broaden access to improved sanitation in SSA? Which aspects of institutions matter the most? Do the answers to these questions differ with respect to urban and rural areas?

The relevance of institutional quality is illustrated in Figure 2.1.2. The figure uncovers the relationship between access to sanitation and six measures of institutional quality. The measures of quality of institutions are Voice and Accountability, Political Stability, Government Effectiveness, Regulation Quality, Rule of Law, and Control of Corruption. The measure are from the World Governance Indicators and are constructed by Kaufmann et al. (2011, henceforth, KKM). The figure shows that institutional quality appear to have a positive association with access to sanitation suggesting that better institutions broaden access to improved sanitation.

Although there exists a growing literature that examines factors that drive access to sanitation, studies that focus on the unique role of institutions remain scant. For instance, studies such as Ndikumana and Pickbourn (2017) and Gopalan and Rajan (2016) investigate foreign aid effectiveness in the water supply and sanitation sector and only mildly account for the role of institutions in their analysis— their primary focus was not the impact of institutions on access to sanitation. In this paper, we present a systematic examination of the effect of institutions on access to improved sanitation. Our paper is closely related to Deacon (2009) who studies how different political regimes (i.e., democratic and autocratic regimes) influence politicians will to provide public goods including sanitation. However, unlike Deacon (2009), we do not focus on political regimes— we focus on individual aspects of institutions and how they impact access to sanitation. Moreover, we extend our analysis to rural and urban areas.

Figure 2.1.2: Correlation Analysis: Access to Improved Sanitation (Total) and Six Proxies for Institutional Quality (World Governance Indicators).



Notes: The data is for for 44 countries averaged from 2002 to 2015. The solid red line represents fitted values. For the institutional variables, we use the standard normal unit measures (i.e. Estimates) for the analysis. Estimates range between -2.5 to 2.5 where higher values corresponds to better outcomes. Pairwise correlation coefficients ranges from 0.22-0.51 with the smallest (largest) coefficient corresponding to voice and accountability (Government Effectiveness). All correlation coefficients are significant at the 5 percent significance level with the exception of that of voice and accountability, which is not significant.

To this end, we estimate a dynamic panel data model to examine the direct impact of institutional quality on access to improved sanitation. We employ panel data of 44 sub-Sahara African countries from 2002-2015 for our empirical analysis. We utilize the aforementioned six different governance indicators from the World Governance Indicators as measures of institutional quality and we use the dynamic panel system Generalized method of moment (GMM) estimator proposed by Blundell and Bond (1998). The following results emerge: First, we find that better institutions broaden access to improved sanitation. Specifically, an increase in the control of corruption, improvement in regulatory quality, and rise in voice and accountability induces an economically large, and a statistically significant positive effect on access improved to sanitation. On the other hand, political stability does not appear to have any significant impact on access to improved sanitation in SSA. Second, we find a dichotomy between rural and urban areas in which aspects of institutions increase access to sanitation. More precisely, regulatory quality, government effectiveness, control of corruption, and rule of law all have a positive impact on access to improved sanitation in rural areas. In contrast, only voice and accountability matter in urban areas. These findings reveal that the capacity of government to implement good and sound policies are relevant for promoting access to improved sanitation in rural areas, the populace's ability to participate in selecting government and expressing freedom through associations and free media is what drive access to sanitation in urban areas. Third, robustness exercises generally show that these conclusions hold for alternative measures of institutions, econometric specification of the model, and the potential endogeneity of institutions.

The rest of Chapter 2 proceeds as follows. Section 2.2 describes the data and the variables of interest. Section 2.3 discusses the estimation procedure. Section 2.4 presents and discusses the benchmark results and the subsequent robustness analysis.

Section 2.5 examines the role of institutional quality in improving access to sanitation in rural and urban areas. Section 2.6 concludes.

2.2 Data and Variables of Interest

The empirical analysis in the paper employs panel data of 44 sub-Saharan African countries from the period 2002-2015.[1] The dependent variable of interest is Access to Improved Sanitation (AIS) and it is measured by the percentage of the population with access and using improved sanitation facilities. Table 2.2.1 presents the descriptive statistics of the variables used in the empirical analysis. In what follows, we present a short description of the key explanatory variable and other control variables used in the empirical estimation.

Table 2.2.1: Summary Statistics

Variable	Mean	Standard Dev.	Minimum	Maximum
Access to Sanitation, Overall	33.64	22.33	7.40	98.40
Access to Sanitation, Rural	25.83	23.66	2.90	98.40
Access to Sanitation, Urban	45.71	20.75	16.70	98.40
Voice and Accountability	-0.59	0.73	-2.23	0.97
Political Stability	-0.52	0.88	-2.70	1.20
Government Effectiveness	-0.75	0.61	-1.85	1.05
Regulatory Quality	-0.67	0.61	-2.24	1.13
Rule of Law	-0.71	0.63	-1.85	1.08
Control of Corruption	-0.67	0.63	-1.77	1.22
Gov't Consumption/GDP	15.37	6.66	2.05	46.60
log of GDP per capita	6.95	1.13	4.73	10.03
Age dependency ratio	83.53	14.48	41.28	111.67
Inflation rate	7.88	11.53	-29.69	103.82
Population density	91.99	125.86	2.41	621.97
Aid to water & sanitation/GDP	0.27	0.65	8.45e-06	8.71
Foreign direct investment/GDP	5.96	13.42	-6.05	159.72

[1] See appendix B.2 for the list of countries employed in the analysis.

2.2.1 Measure of Institutional Quality (MIQ)

The principal question in this paper is whether better institutions promote access to improved sanitation. We therefore employ six broad dimensions of governance that in turn reflect the quality of institutions. Particularly, we utilize data from the World Governance Indicators (WGI) constructed by KKM. The institutional variables are as follows: (1) *Voice and Accountability (Voice)*: It captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. (2) *Political Stability and Absence of Violence/Terrorism (Political Risk)*: It captures perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. (3) *Government Effectiveness (Government)*: It represents perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. (4) *Regulatory Quality*: This measures the perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. (5) *Rule of Law:* It captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. (6) *Control of Corruption (Corruption)*: This measure captures the perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.

These indicators are reported in standard normal units, which range from approximately -2.5 to 2.5, and in percentile rank, which ranges from 0 to 100. Higher values correspond to better outcomes and higher levels of institutional quality. In our benchmark analysis, we use the standard normal units as our yardstick measure for institutional quality. We report the results from the percentile rank measure as part of the robustness exercise. While the percentile rank ranges from 0 (lowest) to 100 (highest), we follow Acemoglu et al. (2008) and Asiedu and Lien (2011) and normalize the percentile rank to lie between 0 and 1. It is important to note that the rank is still preserved after this normalization. Specifically, 0 and 1 represent worst and best outcomes, respectively.

For each of the six institutional variables, we hypothesize that they will have a positive relationship with access to sanitation. For instance, one will expect that the higher the degree of which citizens are able to participate in selecting the governments and have the ability to express themselves freely by demanding or advocating for basic needs, the higher the likelihood that a larger fraction of the populace will have access to improved sanitation. Similarly, a higher degree of government effectiveness can broaden access to improved sanitation. This is because with less political pressures from interest groups, governments are more likely to inact policies that will provide uniform access to improved sanitation that will serve all citizens regardless of political or cultural affiliation. Moreover, access to sanitation is likely to be higher in countries with stronger political stability, rule of law, regulatory quality, and control of corruption.

2.2.2 Other Control Variables

Now let's turn our attention to the key control variables for the empirical analysis. To make the analysis informative, we categorize the control variables into two groups: (1) domestic variables, and (2) non-domestic variables. The domestic variables, which can also be thought of as core variables, are domestic factors that may determine access to sanitation. The non-domestic variables are external factors such as foreign aid that may facilitate access to sanitation. The rationale behind this strategy is twofold:

First, recent studies have focused primarily on foreign aid while controlling for some institutional variables. By focusing exclusively on domestic determinants of access to sanitation, we are able to assess the unfettered effect of the role of institutional quality. Specifically, we address the question of whether domestic factors alone can increase access to improve sanitation. Second, it is only natural to begin the analysis by investigating the primary determinants of access to sanitation, which in this case will be within-country factors. We later include the non-domestic variables in the analysis.

2.2.2.1 Domestic (Core) Variables

Following the literature, for instance (Gopalan and Rajan, 2016) and (Ndikumana and Pickbourn, 2017), we include the following key domestic variables in our regression analysis.

- *GDP per capita.* This measures the income level as well as the overall economic development in the country. We expect a positive relationship between GDP per capita and improved access to sanitation. Specifically, high (low) income levels will be positively associated with higher (lower) access to improved sanitation.

- *Population density.* It measures the density of population. This variable is included to control for the size or population of the countries of interest. For this variable, its relationship with access to sanitation can be positive or negative. A positive relationship may arise because higher population density could mean lower administrative costs, which may translate to better access to improved sanitation facilities for a larger segment of the population (Gopalan and Rajan, 2016). Since sanitation is a rival good— i.e., for a given physical area with limited facilities, the consumption by one consumer may prevent simultaneous consumption by another consumer— higher population density will be associated with lower access to sanitation. Consequently, if assessed from the rival good perspective, we would expect a negative relationship between population density and access to sanitation.

- *Age dependency ratio.* This is measured as the ratio of dependents— people younger than 15 or older than 64— to the working-age population — those ages 15–64. Naturally, given the limited public resources in SSA countries, one would expect that a high dependency ratio would be negatively associated with access to sanitation (Ndikumana and Pickbourn, 2017). However, it is important to note that the selected period for our analysis coincides with the Millenium Development goals (MDGs) era, which was characterized by a global and coordinated effort to advance social development in developing countries. Consequently, it will not be a surprise for one to expect that a higher dependency ratio may induce the provision; hence, access to improved sanitation.

- *Inflation.* Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. This variable captures the well-being of the economy. A moderately high (or low) inflation rate can be a signal of a robust economy. However, a very high inflation signals an uncertain or unfavorable economy. Similarly, a severely low inflation can be seen as a weakening macro-economy. In general, however, we expect that a favorable macroeconomic environment will facilate access to improved sanitation.

- *Government Expenditure.* It is measured as a percentage of GDP, and it is defined as general government final consumption expenditure which includes all public current expenditures for purchases of goods and services (including compensation of employees). The variable captures government size and serves as a broad proxy for the share government expenditure to social expenditure, which includes the sanitation sector. We do expect an positive association between government expenditure and access to sanitation facilities.

2.2.2.2 Non-Domestic Variables

Below, we provide description for the two non-domestic variables employed for the empirical analysis.

- *Aid to Water and Sanitation.* This is defined as aid targeted to the water and sanitation sector by recipient country. Given SSA's dependency on foreign aid, we include total aid targeted to the water and sanitation sector. We could have used data on aid to the sub-sector, sanitation. However, data is limited and unavailable for several years. More importantly, as argued by Ndikumana and Pickbourn (2017), using total aid to the sector, water and sanitation, instead of the sub-sector is intuitive because access to water and access to sanitation are likely to be interdependent, and aid to one sub-sector is likely to have an impact on access in the other subsector. Consider for instance, improvements in water infrastructure. This may facilitate access to improved sanitation because access to water directly facilitates the use of water-reliant sanitation systems. With prior knowledge from previous studies, we expect a positive aid-access to sanitation relationship. However, we do not rule out an unexpected effect such as a non-significant relationship.

- *Foreign Direct Investment.* It represents the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. These are new investment inflows less disinvestment in the reporting economy from foreign investors expressed as a share of GDP. We use this as a proxy for economic openness (Gopalan and Rajan, 2016). As with foreign aid, we hypothesize a positive relationship between greater foreign direct investment inflows and enhanced access to improved sanitation facilities.

2.2.3 Robustness Variables

2.2.3.1 Alternative Institutional Measures

The aforementioned institutional indicators do not by themselves reflect the complete level of institutional quality in a particular country. Instead, the individual measures of institutional quality are likely to work in synchronization to influence the provision of important goods such as sanitation. We therefore construct three aggregate indices of institution, each of which are composites of the six individual governance indicators. The first aggregate measure comes from the standard normal units, and it is constructed by taking an arithmetic average of all the six variables. This measure therefore ranges between -2.5 to 2.5, where a higher value reflect high quality of institutions. The second and third aggregate measures are constructed by applying an arithmetic and geometric mean respectively to the normalized percentile rank measures. The arithmetic measures inherently imply that the individual institutional indicators are perfect substitutes for each other. The geometric measure assumes that the individual institutional measures are imperfect substitutes.

The constructed aggregate measures are as follows: `Aggregate Measure 1`: $Inst^{(1)} = \frac{1}{|I^s|}\sum_{i\in I^s} i$; `Aggregate Measure 2`: $Inst^{(2)} = \frac{1}{|I^r|}\sum_{i\in I^r} i$; `Aggregate Measure 3`: $Inst^{(3)} = \prod_{i\in I^r} i^{\frac{1}{|I^r|}}$. $|.|$ is the cardinality operator, i is the score associated with the standard normal units or percentile rank measure of each governance indicator, $I^k = \{$Voice, Political Risk, Government, Regulation, Rule of Law, Corruption$\}$ and $k \in \{s, r\}$ with s and r representing the standard normal and percentile rank measures, respectively. We employ these aggregate measures, as well as, the percentile rank of the individual institutional indicators as alternative measures of institutional quality as part of the robustness exercise.

2.3 Estimation Procedure

In this section we estimate a linear dynamic panel-data model to capture the effect of lagged access to sanitation on current access to sanitation. We use the "system" generalized method of moments (GMM) estimator proposed by Blundell and Bond (1998) for the empirical analysis. Among other things, the system GMM addresses the weak instrument problem, which both the conventional instrumental variable estimator and the difference GMM estimator proposed by Arellano and Bond (1991) suffer from (See, Han and Phillips, 2010, for details). Specifically, the system GMM is a more efficient estimator that mitigates the weak instrument problem by using additional moment conditions. However, a well-known disadvantage of the system GMM procedure is that it exhibits the "too many" instrument problem. This instrument proliferation issue can overfit endogenous variables and fail to efface their endogenous components. More importantly, the issue weakens the Hansen J test to detect invalidity of the system GMM instruments (Roodman, 2009a,0).

In particular, Roodman demonstrates that the Hansen J test loses its power when the number of cross-sectional units, N, is less than the number of instruments i—i.e., when the instrument ratio $r = N/i$ is less than 1. Hence, in order to mitigate the spillover issues induced by the instrument proliferation problem, Roodman suggests that, as a minimally arbitrary rule of thumb, the instrument ratio should be greater than or equal to 1 (i.e., $r \geq 1$). This can be done by limiting the lags used in the GMM-style instrument. Without limiting the number of instruments, the instrument ratio is always less than 1 in our case. Thus, in all our baseline regressions, we limit the number of lags used in the GMM-style instruments. Following this strategy, we report the standard test for second order autocorrelation, the Hansen J test for overindentifying restrictions as well as the instrument ratio as advocated by Roodman (2009a) and applied in Asiedu and Lien (2011), for instance.

In summary, we estimate the model in this study by employing the two-step GMM estimator, which is asymptotically efficient and robust to all kinds of heteroskedasticity, Windmeijer-corrected standard errors as in Windmeijer (2005), and orthogonal deviations.[2] Moreover, in all the regressions, the independent variables are treated as strictly exogenous. However, in the robustness exercise, quality of institutions are assumed to be endogenous. We discuss this potential endogeneity of institutions in Section 2.4.4. Finally, we exclusively employ internal instruments in all the regressions. More precisely, under the system GMM estimator, the forward orthogonal deviations of the exogenous variables are used as standard instruments. Additionally, the lags of the endogenous variables are used to generate the GMM-style instruments as in Arellano and Bond (1991).

2.4 Results

We want to uncover the direct effect of institutional quality on access to sanitation. Accordingly, we estimate the following equation:

$$AIS_{it} = \alpha MIQ_{it} + \sum_{j=1}^{J} \phi_j Z_{ijt}^{d} + \sum_{k=1}^{K} \gamma_k Z_{ikt}^{f} + \lambda_i + \rho AIS_{it-1} + \epsilon_{it}, \qquad (2.4.1)$$

where the subscript i and t refer to countries and time, respectively. The country-specific effect is captured through λ_i. Z_j^d is the domestic control variable j and Z_k^f is the foreign control variable k.

[2] In the context of balanced panels, GMM estimators based on the first difference and orthorgonal deviations return numerically identical coefficient estimates, holding the instrument set fixed (Arellano and Bover, 1995). Nonetheless, as discussed in Roodman (2009a) orthogonal deviations have the added virtue of preserving sample size in panels with gaps.

Table 2.4.2: The Effect of Institutional Quality on *AIS* with Domestic Determinants

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff.	(4) Regulation	(5) Rule of Law	(6) Corruption
MIQ, $\hat{\alpha}$	0.141**	0.106	0.292	0.173**	0.174	0.295*
	(0.016)	(0.296)	(0.109)	(0.010)	(0.151)	(0.058)
AIS_{t-1}	1.012***	0.967***	0.960***	0.984***	0.981***	0.971***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.009	0.017**	0.015	0.012*	0.013	0.012
	(0.218)	(0.046)	(0.163)	(0.079)	(0.133)	(0.209)
GDP per capita	-0.105*	0.250*	0.335**	0.101	0.135	0.252*
	(0.062)	(0.089)	(0.046)	(0.240)	(0.170)	(0.077)
Age Dependency Ratio	0.006	-0.008	-0.008	-0.005	-0.004	-0.003
	(0.251)	(0.486)	(0.644)	(0.573)	(0.735)	(0.812)
Inflation (%)	0.002	0.003	0.002	0.002	0.002	0.002
	(0.250)	(0.271)	(0.535)	(0.199)	(0.428)	(0.522)
Population Density	-0.001	0.002**	0.003*	0.001	0.001	0.002**
	(0.216)	(0.023)	(0.076)	(0.174)	(0.122)	(0.021)
Constant	0.140	-0.050	-0.295	0.404	0.143	-0.340
	(0.838)	(0.977)	(0.886)	(0.739)	(0.925)	(0.860)
Hansen J test (p-value)[a]	0.640	0.355	0.300	0.441	0.195	0.243
Serial correlation test (p-value)	0.162	0.276	0.199	0.346	0.276	0.362
Observations	541	541	541	541	541	541

Notes: p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test, the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

[a] The no. of instruments, i, and no. of countries N used in all the regression is 42 and 44, respectively. The implied instrument ratio, r, is 1.05.

As previously discussed, we begin by estimating Eq. (2.4.1) without Z^f_{ikt}. The parameter of interest, $\hat{\alpha}$, measures the direct effect of changes in institutional quality on access to improved sanitation. Table 2.4.2 presents the benchmark results with only domestic variables as controls. It is evident from the table that all institutional variables have a positive impact on access to sanitation. However, only voice and accountability, regulatory quality, and corruption control have statistically significant estimates. Specifically, a 10% increase in voice and accountability, regulatory quality, or corruption control increases the percentage of people with access to improved sanitation by 1.4, 1.7, and 2.95 percentage points, respectively.[3] Conversely, the

[3]The impact of control of corruption is consistent with similar findings in Gyimah-Brempong and de Camacho (2006) who find that curbing corruption induces growth in SSA.

impact of political stability and absence of violence, government effectiveness, and rule of law on access to sanitation are not statistically different from zero. These results reveal that overall, the extent to which a country's citizens are able to participate in selecting their government and freely express themselves; formulate and implement sound policies and regulation, or effectively control the extent to which public power is exercised for private gain promote access to improved sanitation.[4]

These findings are in contrast with Ndikumana and Pickbourn (2017) who find a negative effect of government stability on access to sanitation. On the other hand, the non-significant impact of government effectiveness and rule of law on access to sanitation is consistent with findings in (Gopalan and Rajan, 2016). However, our results differ from (Gopalan and Rajan, 2016) in the case of the impact of regulatory quality. Specifically, Gopalan and Rajan find a negative effect of regulatory quality on access to sanitation. Importantly, the results shed light on the relevance of voice and accountability and control of corruption— two institutional variables not considered in the aforementioned studies— in facilitating access to improved sanitation.

To further highlight the importance of these benchmark results, we focus on the three institutional measures that have statistically significant impact on access to sanitation. We use a counter factual exercise to illustrate this. Consider two distinct countries— Mauritius and DR Congo. These two countries are different in terms of the level of institutional quality. More precisely, Mauritius has an overall level of institutional quality that is higher than DR Congo, a country with low levels institutional quality (See, appendix B.2 in the Appendix for a comparison). Applying the results in Table 2.4.2 suggest that if voice and accountability in DR Congo increased from its average of -1.42 to the level of Mauritius, 0.86, then the percentage of the population with access to improved sanitation will increase by 0.32 percentage points

[4]Our findings support the idea that enhancing regulatory quality can help create incentives for start-ups and innovation in the sanitation industry. This is in line with Lipscomb and Schechter (2018) who find that mobile payment systems can help in reducing market power inefficiencies in the market of sanitation cleaning services in Senegal.

(i.e., $\Delta AIS = \hat{\alpha} \cdot \Delta MIQ = 0.141 \cdot (0.86 - (-1.42)) \approx 0.32$) in DR Congo. Similarly, an improvement in regulatory quality or an increase in control of corruption in DR Congo to the levels of Mauritius will increase access to sanitation by 0.38 and 0.52 percentage points, respectively. Between 2010 and 2015, DR Congo only experienced an average increase of 1.6 percentage points in the percentage of its population who had access to sanitation. Thus, while these values appear marginal, they have strong implication for access to improved sanitation.

Additionally, as shown in Table 2.4.2, apart from the regression with *voice and accountability* (Column 1), the estimated coefficient for the lagged dependent variable $\hat{\rho}$ is significant and less than unity (albeit close) in all the other regressions. Generally, the latter strongly justifies the use of a dynamic system GMM. More importantly, notice that for the stable lagged sanitation coefficients (i.e., $0 < \hat{\rho} < 1$), the long-run impact of a unit increase in institutional quality on access to improved sanitation is given by $\frac{\hat{\alpha}}{1-\hat{\rho}}$, which also implies that $\hat{\alpha} < \frac{\hat{\alpha}}{1-\hat{\rho}}$. Hence, in the long run a unit increase in regulatory quality or control of corruption will increase the percentage of the population with access to improved sanitation by 10.8 and 10.2 percentage points, respectively.

We now turn our focus to the control variables in Table 2.4.2. The results are mixed. Specifically, government expenditure has a consistent positive impact on access to sanitation. On the other hand, an increase in GDP per capita appear to be positively associated to access to improved sanitation for all the regressions except for the regression with voice and accountability. Age dependency ratio and inflation on the other hand do not have any statistically significant impact on access to sanitation. As expected, population density appear to have positive and statistically significant effect on access to improved sanitation.[5]

[5] Although we limit the number of lags of the dependent variable used in instrumentation to 2, we conduct sensitivity analysis by using different number of lags as instruments (i.e., 1, 3, and 4). Generally, we find similar results as in Table 2.4.2. Results are available upon request.

Table 2.4.3 presents the results for the regressions that account for foreign variables. The results are similar to those in Table 2.4.2 with three notable differences. First, the coefficient on regulatory quality is now statistically not different from zero. Second, while the coefficient of voice and accountability increased in size, the coefficient of corruption control is now quantitatively smaller but more significant. Third, the estimated coefficient for the lagged dependent variable is now consistently greater than 1 for all the regression. From a technical perspective, these results are not surprising as including the two foreign variables as additional control variables increases the number of instruments. As discussed earlier, high instrument count can in general lead to estimation issues that can directly or indirectly affect parameter estimates.[6] From an economic perspective, the results suggest that in the absence of foreign variables, more dimensions of institutions can positively impact access to sanitation. That is, domestic variables alone can promote access to improved sanitation.

Moreover, it is clear that the coefficient of aid to water and sanitation is positive but not statistically different from zero in all the regressions— a result similar to those found in Bain et al. (2013) but in contrast to those in Gopalan and Rajan (2016). Also, FDI does not appear to have any significant impact on access to sanitation. These findings do suggest that domestic variables, particularly, institutional quality may be a lead determinant of access to sanitation.

[6]For instance, Roodman (2009b) points out how a high instrument count can lead the two-step GMM, which we employ in this paper, far from theoretically efficient ideal.

Table 2.4.3: The Effect of Institutional Quality on *AIS* with Domestic and Foreign Determinants

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruptoin
MIQ, $\hat{\alpha}$	0.228**	0.060	0.159	0.131	0.190	0.259**
	(0.022)	(0.293)	(0.114)	(0.337)	(0.133)	(0.018)
AIS_{t-1}	1.041***	1.015***	1.005***	1.025***	1.023***	1.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.004	0.010	0.011*	0.008	0.005	0.007
	(0.733)	(0.248)	(0.079)	(0.445)	(0.523)	(0.366)
GDP per capita	-0.328***	-0.128**	-0.037	-0.216***	-0.186***	-0.054
	(0.000)	(0.017)	(0.509)	(0.000)	(0.001)	(0.410)
Age Dependency Ratio	0.019**	0.007	0.005	0.008	0.011	0.009
	(0.024)	(0.243)	(0.427)	(0.261)	(0.163)	(0.230)
Inflation (%)	0.002	0.002	0.002	0.002	0.002	0.002
	(0.314)	(0.168)	(0.241)	(0.187)	(0.357)	(0.339)
Population Density	-0.003***	-0.001	-0.001	-0.002**	-0.002**	-0.001
	(0.007)	(0.177)	(0.410)	(0.021)	(0.014)	(0.235)
Aid to Water and sanitation (% GDP)	0.026	0.057	0.063	0.054	0.053	0.059
	(0.460)	(0.159)	(0.120)	(0.182)	(0.137)	(0.103)
FDI (% GDP)	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001
	(0.765)	(0.365)	(0.542)	(0.793)	(0.825)	(0.204)
Constant	-0.026	0.160	0.015	0.459	0.142	-0.163
	(0.978)	(0.810)	(0.986)	(0.609)	(0.873)	(0.860)
Hansen J test (p-value)[a]	0.317	0.651	0.370	0.525	0.457	0.473
Serial correlation test (p-value)	0.020	0.094	0.075	0.065	0.047	0.107
Observations	513	513	513	513	513	513

Notes: p-value in parentheses. *** p <0.01, ** p <0.05, * p <0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test, the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

[a] The no. of instruments, i, and no. of countries N used in all the regression is 44 and 44, respectively. The implied instrument ratio, r, is 1.

2.4.1 Robustness Regressions

In this section we provide robustness checks to further confirm the relevance of institutional quality in facilitating access to improved sanitation. In the robustness exercise we focus on the regressions that utilize the domestic regressands. For the regression that treat institutions as endogenous, we report the summary of the results with both domestic and foreign variables. Below, we present and discuss the results for the robustness exercises.

2.4.2 Alternative Institutional Measures

We start the robustness analysis by employing alternative measures of institutional quality. First, we utilize the percentile rank measure of governance which offers an alternative to the standard normal units. The percentile rank measure ranges from 0 to 100. However, as discussed earlier, we normalized it to lie between 0 and 1.

Table 2.4.4: The Effect of Institutional Quality on *AIS*, Percentile Rank Measure

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff.	(4) Regulation	(5) Rule of Law	(6) Corruption
MIQ, $\hat{\alpha}$	0.489**	0.585	0.889	0.458**	0.462	0.758*
	(0.034)	(0.215)	(0.104)	(0.033)	(0.249)	(0.075)
AIS_{t-1}	1.008***	0.962***	0.960***	0.980***	0.973***	0.971***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.010	0.018*	0.014	0.015**	0.016*	0.012
	(0.160)	(0.078)	(0.197)	(0.036)	(0.090)	(0.158)
GDP per capita	-0.078	0.292**	0.322*	0.138	0.207*	0.259*
	(0.208)	(0.049)	(0.060)	(0.121)	(0.076)	(0.066)
Age Dependency Ratio	0.006	-0.010	-0.007	-0.006	-0.007	-0.003
	(0.190)	(0.379)	(0.655)	(0.449)	(0.587)	(0.770)
Inflation (%)	0.002	0.002	0.002	0.002	0.002	0.002
	(0.190)	(0.436)	(0.539)	(0.308)	(0.334)	(0.527)
Population Density	-0.001	0.003**	0.003*	0.001*	0.002*	0.002**
	(0.367)	(0.026)	(0.071)	(0.094)	(0.065)	(0.024)
Constant	-0.165	-0.354	-0.682	0.079	-0.182	-0.804
	(0.795)	(0.820)	(0.729)	(0.943)	(0.916)	(0.643)
Hansen J test (p-value)[a]	0.589	0.366	0.377	0.465	0.202	0.304
Serial correlation test (p-value)	0.185	0.280	0.210	0.306	0.248	0.246
Observations	541	541	541	541	541	541

Notes: p-value in parentheses. *** p <0.01, ** p <0.05, * p <0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test, the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

[a] The no. of instruments, i, and no. of countries N used in all the regression is 43 and 44, respectively. The implied instrument ratio, r, is 1.02.

We also employ three composite measures of institutional quality constructed from the individual six indicators described in section 2.3 as our main regressand. Notice that the individual indicators provide highly specific and to a large extent disaggregated information about a particular dimension of governance; hence, institutional quality. These composite measures therefore provide an overall level of institutional quality in the countries under consideration. The results from the percentile rank and composite measures of institutional quality are presented in Table 2.4.4 and Table 2.4.5, respectively.

Table 2.4.5: Benchmark Results using Aggregate Measures of Institutional Quality

VARIABLES	$\text{Inst}^{(1)}$ (Arithmetic)	$\text{Inst}^{(2)}$ (Arithmetic)	$\text{Inst}^{(3)}$ (Geometric)
MIS, $\hat{\alpha}$	0.206*	0.784	0.715*
	(0.067)	(0.138)	(0.074)
AIS_{t-1}	0.982***	0.976***	0.977***
	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.012	0.012	0.012
	(0.127)	(0.176)	(0.123)
GDP per capita	0.114	0.164	0.159
	(0.247)	(0.147)	(0.156)
Age Dependency Ratio	-0.004	-0.006	-0.005
	(0.761)	(0.566)	(0.564)
Inflation (%)	0.002	0.002	0.002
	(0.259)	(0.207)	(0.202)
Population Density	0.001*	0.002**	0.002**
	(0.094)	(0.016)	(0.015)
Constant	0.300	-0.089	-0.105
	(0.863)	(0.954)	(0.943)
Hansen J test (p-value)[a]	0.247	0.392	0.436
Serial correlation test (p-value)	0.319	0.318	0.311
Observations	541	541	541

Notes: p-value in parentheses. *** p <0.01, ** p <0.05, * p <0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test, the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

[a] The no. of instruments, i, and no. of countries N used in all the regression is 42 and 44, respectively. The implied instrument ratio, r, is 1.05.

As can be seen from Table 2.4.4, the effect of institutions on the access to improved sanitation are strikingly similar to the results from the standard normal unit measure. Specifically, Voice, Regulatory quality, and corruption have a positive impact on access to sanitation. Moreover, with the exception of $inst^{(2)}$ the regressions with the composite measures of institutions reveal that the estimated coefficient $\hat{\alpha}$ is significant at the 10% level.

This suggests that the overall level of institutional quality promotes improved access to sanitation both in the short- and long-run (Table 2.4.5). Generally, these findings reinforce our initial conclusion from the benchmark regressions.

2.4.3 Time Fixed Effects

In the benchmark estimations, we did not include time specific effects. Consequently, we control for time specific effects by including time dummies in our benchmark specification in Eq.(2.4.1). Time fixed effects do capture the influence of aggregate trends. Additionally, they help extirpate the effect of business cycles. A downside to including the time specific effects is that it increases the number of instruments employed in the regression, which as previously mentioned may weaken the empirical results. Results are presented in Table 2.4.6. Out of nine regressions with different measures of institutional quality, $\hat{\alpha}$ is significant at the 10% level or better in seven regressions. Again, this shows that institutional quality broadens access to sanitation.

2.4.4 Potential Endogeneity of Institutions

Finally, we control for the possible endogeneity of institutions. In countries with good quality institutions, political incentives that may drive growth in sanitation are the following: sanitation has a social value; sanitation impacts human health, the quality of sanitation increases a country's reputation; sanitation is considered important for state legitimacy; hence, the legitimacy of public institutions. In this sense, there is a genuine likelihood that access to sanitation and institutional quality are codetermined. Moreover, as Rodrik (2004) points out, the most commonly used institutional quality measures are based on surveys of domestic and foreign investors, thus capturing perceptions rather than any of the formal aspects of the institutional setting. This in his view creates two important problems— perceptions are shaped not just by institutional environment, but also by many other aspects of the economic envi-

Table 2.4.6: Benchmark Results with Time Fixed Effects

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.169*	0.071	0.183**	0.181	0.206*	0.294***	0.255**	0.697*	0.701**
	(0.091)	(0.268)	(0.049)	(0.124)	(0.086)	(0.010)	(0.022)	(0.065)	(0.039)
AIS_{t-1}	1.026***	0.992***	0.984***	1.004***	1.004***	0.988***	1.007***	1.002***	1.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.007	0.010	0.008	0.005	0.005	0.001	0.003	0.004	0.004
	(0.494)	(0.301)	(0.372)	(0.543)	(0.602)	(0.927)	(0.756)	(0.687)	(0.628)
GDP per capita	-0.302**	0.031	0.121	-0.124	-0.088	0.089	-0.142	-0.082	-0.073
	(0.028)	(0.854)	(0.448)	(0.437)	(0.508)	(0.629)	(0.329)	(0.602)	(0.628)
Age Dependency Ratio	0.006	-0.002	-0.001	-0.002	0.001	0.002	0.002	0.001	0.001
	(0.482)	(0.795)	(0.855)	(0.716)	(0.854)	(0.785)	(0.795)	(0.827)	(0.895)
Inflation (%)	0.002	0.001	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000
	(0.355)	(0.764)	(0.960)	(0.975)	(0.835)	(0.843)	(0.901)	(0.892)	(0.999)
Population Density	-0.002*	0.000	0.001	-0.001	-0.001	0.001	-0.001	-0.000	-0.000
	(0.053)	(0.702)	(0.456)	(0.567)	(0.498)	(0.495)	(0.512)	(0.780)	(0.793)
Constant	1.139	0.372	0.028	1.347	0.819	0.069	1.084	0.458	0.500
	(0.240)	(0.759)	(0.983)	(0.234)	(0.429)	(0.954)	(0.336)	(0.645)	(0.614)
Hansen J test (p-value)[a]	0.883	0.722	0.843	0.756	0.728	0.762	0.775	0.703	0.742
Serial correlation test (p-value)	0.141	0.511	0.449	0.408	0.362	0.737	0.383	0.371	0.339
Observations	541	541	541	541	541	541	541	541	541

Notes: p-value in parentheses. *** p <0.01, ** p <0.05, * p <0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

[a] The no. of instruments, i, and no. of countries N used in all the regression is 53 and 44, respectively. The implied instrument ratio, r, is 0.83.

ronment, creating endogeneity and reverse causality issues, and even when causality is established, the results do not indicate the specific institutional design that led to the measured outcome (Catrinescu et al., 2009). We therefore address this potential endogeneity issue by explicitly specifying all the institutional measures employed in this paper as endogenous variables in the benchmark regressions.

Despite limiting the number of lags used in the GMM-style instruments, treating institutions as endogenous naturally increases the number of instruments. Hence, this is the only set of regressions in which the instrument ratio is less than 1. We acknowledge these potential issues that arise and report the results. The summary results are presented in Table 2.4.7. The full results are available in the appendix. Evidently, all the regressions show that institutions have a positive and statistically significant effect access to improved sanitation.

Table 2.4.7: Summary Results with Institutions Treated as Endogenous

VARIABLES	Voice	Political	Gov. Eff	Regulation	Rule of Law	Corruption	Insti$^{(1)}$	Insti$^{(2)}$	Insti$^{(3)}$
MIQ, $\hat{\alpha}$ (Domestic)	0.953***	0.809***	1.377**	1.578***	1.513**	1.363***	1.609**	5.410***	4.621**
	(0.007)	(0.003)	(0.020)	(0.029)	(0.029)	(0.001)	(0.027)	(0.007)	(0.013)
MIQ, $\hat{\alpha}$ (Foreign)	0.976***	0.680***	1.246***	1.310***	1.329***	1.453***	1.471***	4.532***	4.408***
	(0.001)	(0.000)	(0.003)	(0.009)	(0.005)	(0.001)	(0.006)	(0.001)	(0.001)

Notes: p-value in parentheses. *** p <0.01, ** p <0.05, * p <0.1. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 1. Full results and tests details are reported in Tables **??** and **??** in the Appendix.

2.5 Rural vs Urban

There exists a rural-urban gap in achieving improved access to sanitation in almost all the countries in our sample. In fact, as can be seen in appendix B.2, there is a clear rural-urban gap in terms of the percentage of the population who have access to improved sanitation. Gopalan and Rajan (2016) argues that this rural-urban gap in achieving improved access to sanitation can be attributed to the different capacity of institutions in rural and urban areas. We therefore investigate whether: (a) the role of institutions in facilitating access to improved sanitation differ in rural and urban areas, and (b) if they do, which institutional qualities matter.

Table 2.5.8 presents summary results of the impact of institutional quality on access to improved in rural and urban areas. The results reveal that institutional quality promote access to improved sanitation in rural and urban areas. However, there is a stark contrast between urban and rural areas as to which aspects of institutional qualities matter for improving access to sanitation. In particular, the only institutional variable that drive improved sanitation in urban areas is voice and accountability. In contrast, besides political stability and voice and accountability, all other aspects of institutions— i.e., corruption control, regulatory quality, government effectiveness, rule of law, and the three aggregate institutional variables— positively impact access to sanitation in rural areas. This implies that when it comes to access to sanitation, urban areas are the main beneficiaries of citizens' ability to participate in selecting government.

Table 2.5.8: Summary Results of the Impact of Institutions on Access to Sanitation, Rural vs Urban

VARIABLES	Voice	Political	Gov. Eff	Regulation	Rule of Law	Corruption	Inst$^{(1)}$	Inst$^{(2)}$	Inst$^{(3)}$
Rural Areas									
MIQ, $\hat{\alpha}$ (Domestic)	0.119	0.054	0.258*	0.184**	0.232**	0.402***	0.259**	0.889**	0.790**
	(0.169)	(0.473)	(0.075)	(0.020)	(0.026)	(0.001)	(0.019)	(0.019)	(0.019)
MIQ, $\hat{\alpha}$ (Foreign)	0.142	0.059	0.271***	0.196**	0.209**	0.409***	0.250***	0.820***	0.742***
	(0.113)	(0.349)	(0.004)	(0.028)	(0.016)	(0.000)	(0.006)	(0.004)	(0.008)
Urban Areas									
MIQ, $\hat{\alpha}$ (Domestic)	0.283**	0.069	0.072	0.192	0.132	0.075	0.164	0.376	0.422
	(0.015)	(0.339)	(0.629)	(0.141)	(0.280)	(0.421)	(0.192)	(0.321)	(0.265)
MIQ, $\hat{\alpha}$ (Foreign)	0.254**	0.047	0.054	0.155	0.102	0.011	0.163	0.373	0.420
	(0.011)	(0.462)	(0.717)	(0.358)	(0.447)	(0.933)	(0.258)	(0.424)	(0.387)

Notes: p-value in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2. Full results and tests details are reported in Tables **??**, **??**, **??**, and **??** in the Appendix.

More precisely, the voting power of rural areas does not appear to increase their access to sanitation. However, the capacity of the government to implement good and sound policies matter for improving sanitations in rural areas. This is to say that good governance in implementing policies matters more than the voting power in driving improved access to sanitation in rural areas.

2.6 Concluding Remarks

This paper contributes to the expanding literature on the factors that affect access to sanitation. We examined the direct effect of institutional quality on access to improved sanitation in sub-Sahara Africa. The baseline results show that better institutions broaden access to improved sanitation with voice and accountability, regulatory quality, and control of corruption playing the most significant roles. There is, however, a clear contrast between urban and rural areas with regards to the aspects of institutional qualities that matter for increasing access improved to sanitation. In urban areas, the only institutional variable that promotes access to sanitation is voice and accountability. In rural areas, this institutional variable does not appear to affect access sanitation. This implies that the populace's ability to participate in selecting government and expressing freedom through associations and free media do not appear to increase access to sanitation in rural areas. Instead, strong corruption control, rule of law, and the capacity of the government to implement good and sound policies promote access to improved sanitations in rural areas.

Policy-wise, to achieve the Sustainable Development Goal (SDG) relating to access to improved sanitation for all, our results strongly suggest several aspects of institutions to work effectively. Specifically, competitive political parties, an independent judiciary, a vigilant free press, oversight by parliamentary bodies, and constitutional checks and balances preventing the abuse of power by the executive officials are important in broadening access to sanitation. Furthermore, elections with integrity are the core mechanism keeping or restoring greater accountability of office-holders to voters. Accordingly, access to sanitation can become an important political agenda for executives if elections truly reflect the aspirations and voice of the people, including the less disadvantaged ones living in rural areas.

Finally, because progress in rural areas is central to achieving this SDG, it is crucial to find effective ways to shape the institutional arrangements in rural areas as a positive and necessary way forward. Undertaking political and institutional reforms at local and national levels with the aim of improving government effectiveness, fighting corruption, and promoting a citizen-centric approach to public administration should not be overlooked in developing strategies for broadening access to sanitation in sub-Saharan countries. It is worth mentioning that the SDG goal 16 has a target to promote accountable and inclusive institutions. Therefore, a long-term institutional approach to solving sanitation issues in rural areas should include fostering a decentralization of political power to rural electoral jurisdictions, strengthening rural institutions that uphold human rights, and promoting a friendly regulatory environment for entrepreneurship and start-ups focusing on business opportunities related to sanitation issues.

CHAPTER 3

DO TEACHER QUALITY AND LANGUAGE OF INSTRUCTION AFFECT STUDENT LEARNING DEPRIVATION? EVIDENCE FROM MAURITANIA AND SENEGAL

3.1 Introduction

Following Hanushek (1979), the literature on student learning (i.e., skills acquisition) has gained more importance, especially at the basic education level.[1] Education appears to accelerate economic growth by boosting student learning and skills (see Glewwe et al. (2014) and Hanushek and Woessmann (2012)). In the realm of international education, most policies aim to improve student learning. For example, in 2019, the World Bank introduced a Learning Target, designed to emphasize one fundamental skill at the core of the Sustainable Development Goals (SDGs) aspirations[2]: the ability to read by age 10 with at least a minimum level of comprehension. Ensuring that all students learn is essential to achieving the ambitious SDG targets and to building human capital. Indeed, a growing list of evidence shows that learn-

[1]Basic education refers to pre-primary, primary and lower secondary education levels.

[2]The Sustainable Development Goal 4 makes the following commitment: by 2030, the signatories will ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. The various targets under this goal cover the educational landscape, starting with universal access to quality early childhood development and preschool and extending to equal access to affordable university education. But the very first of these commitments is Target 4.1, which is to ensure that all girls and boys complete free, equitable, and quality primary and secondary education leading to relevant and effective learning outcomes.

ing, not just schooling, matters in how education affects earnings (see Hanushek and Woessmann (2015) and Valerio et al. (2016) for example).

Despite many efforts, learning levels among the vast majority of children in developing countries often meet neither the expectations of national curricula, nor the much more basic levels of competence tested in both national and regional standardized assessments. The scale of this learning crisis has been well documented by Sandefur (2018) and World Bank (2018), among others. Recently, UNESCO (2017) estimated that 617 million children around the world are not learning at basic levels. In addition, World Bank (2019) has estimated about half the children in low and lower-middle income countries are learning deprived, as they cannot read a simple paragraph at age ten, yet little is known about which factors drive learning deprivation. This is primarily due to the absence of data that provides sufficient information to identify the determinants of student learning. As argued by Hanushek (1979), proximate determinants of learning include student preparation, teacher skills and motivation, the availability of relevant school inputs, and the school management (see also World Bank (2018)). The language of instruction has also been identified as a potential determinant (Brock-Utne (2007); Collier and Thomas (2017); and World Bank (2021)). In general, these conclusions are based on empirical studies, and the causal impact of teacher quality and language of instruction on the student learning is not known.

In this paper, I analyze the impact of teacher quality and language of instruction on learning deprivation by using a unique dataset from Senegal and Mauritania.[3] In the existing literature on student learning, the term *learning deprivation* usually means that a student's reading competency is below the minimum proficiency level. I depart from the general literature on education production functions that often uses student achievement (test scores) as the outcome variable. Instead, I focus on

[3] I focus on those two countries due to data limitation.

whether a student acquires a minimum learning proficiency. Learning deprivation is a relatively new concept that is based on the World Bank and UNESCO Institute for Statistics (UIS) new multidimensional indicator learning poverty (World Bank (2019)). Learning deprivation as an outcome variable, reflects the aspiration of Sustainable Development Goal (SDG) 4 that all children must not only be in school, but they must also be learning.

The analysis is made possible by the unique primary school level dataset from Mauritania and Senegal provided by the Service Delivery Indicators (SDI) survey. I exploit three features of the SDI survey. First, the student language test score allows me to measure learning deprivation. Second, the student language test is done in both French and Arabic, which enables one to investigate the impact of the language of instruction. Though French is widely understood and used as an inter-communal language in both countries, especially in the media and business, it is spoken by few Senegalese and Mauritanians as a second language - 37 percent and 13 percent respectively. Arabic is the familiar language and serves as a lingua franca in both countries. Third, the data also provides test scores for teachers, which allows me to measure teacher quality based on teacher subject content knowledge. Moreover, the dataset provides information on students, teachers, school-characteristics, and allows me to control for unobserved factors, such as regional fixed effects.

I use an instrumental variable probit model to estimate the effect of language of instruction and teacher quality on learning deprivation. Teacher quality is endogenous due to the presence of unobserved school-specific characteristics (e.g., school management and the availability of school supplies) and unobserved teacher-characteristics (e.g, teaching methods and teacher traits). These unobserved factors are likely to be correlated with both teacher quality and student learning deprivation. For example, better-motivated teachers could induce more student learning but also accrue more subject knowledge. Therefore, the estimation strategy employs the use of teacher education (i.e., diploma) as an instrumental variable. Teacher education is a past decision and is not influenced by unobserved school characteristics. Even if better schools (e.g., those located in urban areas) may attract teachers with higher education, this does not raise an endogeneity issue because I control for several observed school characteristics (e.g., urban area) and for regional fixed effects. I also control for observed student characteristics. Specifically, I control for whether students attended preschool prior their primary school education (see Hanushek (1979)) in addition to student characteristics, such as age and gender.

The results show that there are strong correlations between teacher quality and learning deprivation and between language of instruction and learning deprivation among students in Mauritania and Senegal. A decrease in the quality of teachers by one percentage point is associated with an increase of the likelihood of a student's being learning deprived by 6.05 percentage points. I also show that the learning deprivation of a student who is taught in French is 98 percentage points higher than that of a student who is taught in a familiar language (i.e., Arabic). These results suggest that policymakers in developing countries should focus on teachers' subject knowledge in teacher recruitment, training, and compensation policies. They also shed light the importance of prioritizing the use of a familiar language versus that of an unfamiliar language in basic education.

Several other papers in the literature point out the role of teachers in student learning and achievement.[4] Important studies estimating the association of teacher quality with student achievement include Hanushek (1971), Hanushek (1992), Rockoff (2004), Glewwe and Kremer (2006), Behrman et al. (2008), and Bau and Das (2020). For example, it has been found that students with great teachers in the United States progress faster through their grades than students with weak teachers (Hanushek (1992) and Rockoff (2004)).

[4] For a review of the experimental literature, see Kremer et al. (2013), Ganimian and Murnane (2016), and Evans and Popova (2016)

In developing countries, the effect of teachers on student learning was estimated to be from 0.14 standard deviations in Uganda, to more than 0.9 standard deviations in India, the equivalent of multiple years of schooling (Buhl-Wiggers et al. (2017) and Bau and Das (2017).

However, the existing evidence on the impact of teacher quality on student achievement is still likely to suffer from bias due to unobserved school-specific characteristics and unobserved teacher-characteristics (see Metzler and Woessmann (2012)). Examples of such bias include incidents where school principals with better leadership traits could organize training sessions and remedial activities that would increase both student and teacher performance; where schools with better physical conditions, equipment, and supplies also have students with higher learning proficiency and better teachers; and where better-motivated teachers stimulate more student learning but also accrue more subject knowledge. Estimates of the effect of teacher quality and other observable teacher characteristics that convincingly address such biases are missing in the literature. This paper complements the literature, as I use an IV methodology to control for possible endogeneity of teacher quality.

Relatively few studies look at the impact of language of instruction on student learning. Trudell and Piper (2013) argue that students learn better in their first language (i.e., one' s mother tongue or a familiar language) than in a second language. Students were also found to be more likely to become proficient in a second language and comfortably absorb academic content (Brock-Utne (2007); Collier and Thomas (2017); and World Bank (2021)). Contrary to the existing literature, this paper exploits a unique feature of the SDI dataset, where students are assessed in both French and Arabic to investigate the impact of language of instruction on learning deprivation. I find that the effect of language of instruction on learning deprivation is larger than that of teacher quality.

The rest of this chapter is structured as follows. The dataset and relevant descriptive statistics are presented in Section 3.2, while the model specification and estimation strategy are discussed in Section 3.3. Section 3.4 shows the results of the impact of teacher quality and language of instruction on student learning. Section 3.5 concludes the paper.

3.2 Data and Descriptive Statistics

The paper uses a primary school-level dataset from the Service Delivery Indicators (SDI) survey from Senegal and Mauritania to estimate the causal effect of teacher quality and language of instruction on student learning deprivation. The SDI survey is an ongoing program that collects information on students, teachers and the availability of key school inputs required to provide quality services (infrastructure, equipment, supplies, etc.). The data is generally collected through visual inspections of 4th-grade classrooms and the primary school premises. The SDI survey also tracks learning outcomes of students and knowledge of teachers based on randomly administered standardized language and mathematic tests. Data were collected in primary schools in 2017 in Mauritania and in 2020 in Senegal. Information was collected from 793 public and 207 private schools, and 9,924 grade 4 students as well as 4,009 teachers to assess learning outcomes and content knowledge. The survey design ensures that this sample is nationally representative with respect to region of country, urbanization, school size, school type, and ethnicity.[5]

In each country, representative surveys of schools were implemented using a multistage, cluster-sampling design. Primary schools with at least one 4th-grade class formed the sampling frame. In each school, 10 students are sampled from a randomly selected grade 4 classroom. The choice to test students who had completed the third

[5] Information on how to obtain data files is available on the SDI website (https://www.sdindicators.org/).

grade was made with a desire to assess cognitive skills at young ages when these are most malleable and a desire to assess the learning outcomes of students who had completed at least some schooling and to assess language learning at a time when all children would have had lessons in the official language of their country (i.e., French). In each school, the students' current (grade 4) teacher, and to the extent possible, previous (grade 3) teacher were selected for testing.

The student test was designed as a one-on-one evaluation, with enumerators reading instructions aloud to students. The student language test, which evaluated ability in both French and Arabic (a familiar language), ranges from simple tasks that tested letter and word recognition to a more challenging reading comprehension test. The test spans items from the first four years of the primary education curriculum.[6] The teacher test consisted of grading mock student tests in language and in mathematics and answering a series of questions on pedagogy. As noted in Bold et al. (2019), this method of assessment (in contrast to exam taking) has the advantage of assessing teachers in a way that is consistent with their regular teaching activities namely, marking student work.

To construct learning deprivation, I use the results of the student language test to which I have applied the *minimum proficiency level* concept. The term *minimum proficiency level* (MPL) is defined by the Global Alliance to Monitor Learning (GAML) in the context of the SDG 4.1.1b monitoring.[7]. At the MPL, students independently and fluently read simple, short narrative and expository texts. They locate explicitly stated information. They interpret and give some explanations about the key ideas in these texts. They provide simple, personal opinions or judgements about

[6] The teacher and student subject tests were designed by experts in international pedagogy and validated against 13 Sub-Saharan African primary curricula (Botswana, Ethiopia, The Gambia, Kenya, Madagascar, Mauritius, Namibia, Nigeria, Rwanda, the Seychelles, South Africa, Tanzania, and Uganda). See Johnson, Cunningham and Dowling (2012) for details.

[7] UNESCO, 2019. https://gaml.uis.unesco.org/wp-content/uploads/sites/2/2019/05/GAML6-REF-2-MLP-recommendations-ACER.pdf

the information, events, and characters in a text[8]. Students are expected to master these simple tasks by the end of grade 4. Hence, applying the definition of the MPL using the SDI language test, is translated as the ability to read at least half a simple 70-words paragraph out loud and correctly answer at least one related basic understanding question. The MPL is consistent with both (i) the national level test score requirement for a grade 4 student to be promoted to grade 5 (i.e., reading at least half a simple 70-words paragraph) and (ii) the World Bank's measurement of Learning Poverty (World Bank (2019)). Based on this definition, a grade 4 student is learning deprived if his/her reading competency falls below the minimum proficiency level.

Concerning the two explanatory variables of interest, I use the average test scores of teachers as a proxy for teacher quality and the language of assessment as a proxy for language of instruction. Teacher quality is measured at the school level and not at the individual level due to the inability to match the samples of students and teachers who were tested. First, each teacher's test score is measured based on his/her ability in marking correctly mock student language and mathematics tests and correctly answering a series of questions on the pedagogy test. A teacher is awarded 1 point if he gives the correct grade (for the mock tests) and correct answers (for the pedagogy test). A teacher's score will then be the sum of the correct grades, and answers divided by the total number of questions and multiplied by 100. Second, I take the arithmetic mean of all teacher test scores at the school level. The average teacher score is constant within a school but varies across schools. The variation across schools is sufficient to capture the average impact of teacher quality.[9] Using teacher test scores as a proxy for teacher quality is critical as teachers need the requisite content knowledge and pedagogical approaches to be good teachers.

[8]idem

[9]The variation between schools is the source of the identification. Using individual data would be better but the dataset does not make this possible given that both students and teachers samples cannot be matched.

I also use the language in which students were assessed as a proxy for the language of instruction. The language test can be administered in French (unfamiliar language) or Arabic (familiar language). A *familiar language* is a language that is spoken first by children in their common environment. Children learn *unfamiliar languages* later in life, mostly in schools. Though French is widely understood and used as an inter-communal language in both countries, especially in the media and business, it is spoken by few Senegalese and Mauritanians as a second language - 37 percent and 13 percent respectively.[10] Arabic usually serves as a lingua franca in Senegal and Mauritania. The fact that the population in both Senegal and Mauritania is almost completely Muslim makes Arabic the recognized and familiar language. Senegal and Mauritania have language of instruction policies in place allowing bilingual curricula in selected familiar languages.[11] In this paper, the binary variable language of instruction takes on the value 1 if the assessment language is French and 0 otherwise.

Appendices C.1 and C.2 report the descriptive statistics of the variables for all observations and students that are either learning deprived or performing better based on their reading competency level. Of the 9,924 grade 4 students in the study population, 5,174 (52.14 percent) were learning deprived and 4,750 (47.86 percent) were not learning deprived. The average age of students in the sample is 11.7 years, and the majority (54 percent) are girls. Only 26 percent of the students categorized as learning deprived attended preschool prior to primary school. More learning deprived students are enrolled in public schools (84 percent) than in private schools and fewer are in schools located in urban areas (40 percent) than in rural areas. 68 percent of the teachers hold at least an upper secondary education diploma (grade 13), compared to either a lower secondary education diploma (grade 10) or no academic diploma.

[10] See, Translators without Borders (2021)

[11] In Mauritania, the curricula at the primary school level is taught in Arabic from grade 1, with a gradual transition to French. In Senegal, French is the primary language for instruction, but there are experiments using Arabic and other familiar languages such as Wolof, Pulaar, and Seereer.

3.3 Model Specification

The goal of this paper is to estimate the impact of teacher quality and using French (as opposed to a familiar language - Arabic) as the language of instruction on learning deprivation among Senegalese and Mauritanian primary students. The dependent variable in the analysis is dichotomous, equal to 1 for learning deprived students and 0 otherwise. Teacher quality is a continuous variable and is given by the average test score of teachers derived from the SDI assessment of teachers. Language of instruction is dichotomous with a value of 1 if French is used as the language of instruction and 0 if Arabic (i.e., a familiar language) [12].

Two identification issues need to be addressed in specifying the model. Since the dependent variable (learning deprivation) takes the form of a binary variable, a probit or logit model is appropriate (Long (1997). The second issue concerns potential endogeneity of teacher quality, caused, for example, by the presence of (i) unobserved school-specific characteristics, such as school management or leadership traits of school principals who could organize training sessions for teachers; the physical condition of classrooms and availability of school supplies that contribute to better learning and teaching environment; and (ii) unobserved teacher characteristics such as teaching method, teacher traits. These unobserved factors are likely to be correlated with both the average test score of teachers (teacher quality) and student learning deprivation (i.e., student performance in reading). This suggests that there is a co-movement between both the dependent variable and teacher quality that can bias the estimation of the causal effect (see Metzler and Woessmann (2012). Although I control for several observed school characteristics (see Table 3.4.1), the teacher quality variable will still be endogenous due to unobserved school characteristics. For example, as argued by Metzler and Woessmann (2012) , the endogeneity may due to

[12] As the language of instruction was not observed, it is assumed that the language in which the student is assessed is the language of instruction.

the correlation between unobserved student characteristics (self-effort, self-attention, self-motivation) and teacher quality. In such a case, controlling for observed school characteristics is not sufficient to address the endogeneity issue.

The previous discussion implies that the best way to address the endogeneity problem would be to control for both unobserved student characteristics and unobserved teacher characteristics.[13] However, this is not possible because since I have a single observation (i.e., test score) per student and per teacher. This would have been possible through a fixed effects model if the students and the teachers were assessed several times, but I cannot add school fixed effects for two reasons. First, adding school fixed effects will lead to an incidental parameter issue as the number of parameters to be estimated grows as the sample size goes to infinity (see Lancaster (2000b)). The second reason is an identification issue, as there is no within-variation in the teacher quality variable in a specific school given that it is constructed as an average across teachers at the school level. As mentioned above, the dataset does not make it feasible to link each teacher to each student. Students and teachers were selected randomly for the assessment and it is not feasible to match both samples.

To eliminate the endogeneity issue, I use a just identified instrumental variables probit model (IVPROBIT) to estimate the impact of teacher quality and language of instruction. Teacher quality at the school level is modeled as a regressor in a recursive simultaneous equations model of the determinants of learning deprivation. The model in this paper is given by the following equations:

$$LD^*_{ij} = \beta_0 + \beta_1 TQ_j + \beta_2 Fr_{ij} + X'_{ij}\beta_3 + u_{ij} \tag{3.3.1}$$

$$TQ_j = \alpha_0 + \alpha_1 TE_j + \alpha_2 Fr_j + X'_j\alpha_3 + v_j \tag{3.3.2}$$

[13]This means that I also control for unobserved school characteristics indirectly.

The observed variable for learning deprivation, LD_{ij} , is related to the latent LD^*_{ij} in Eq.(3.3.1) above in the following manner:

$$LD_{ij} = \begin{cases} 1, & |LD^*_{ij} \geq 0 \\ 0, & |LD^*_{ij} < 0 \end{cases} \tag{3.3.3}$$

Student i in school j is considered learning deprived when the student's reading competency is below the minimum proficiency level. More details on the dependent variable, the explanatory variables, the instrumental and the control variables in the model are in Appendix C.1. Fr is a dummy variable for language of instruction, X is a vector of control variables that affect learning deprivation, TQ_j (the endogenous variable) denotes teacher quality in school j, and TE_j is a dummy that takes the value 1 if a teacher in school j holds at least an upper secondary diploma (the instrumental variable). By assumption, $(u_i, v_i) \sim N(0, \Sigma)$, (i.e., the error terms are jointly normally distributed) and the variance (σ) is normalized to one to identify the model. β_0, β_1, β_2, and β_3, are structural parameters; and α_0, α_1, α_2 and α_3 are reduced-form parameters.

Several reasons justify why TE is exogenous. Unlike teacher quality, TE is a past decision and is not influenced by unobserved school-characteristics, such as school management. On the other hand, even if better schools (for example in urban areas) attract teachers with higher diplomas, this does not raise an endogeneity issue because I control for several observed school characteristics (urban area, school status as public or private, etc.) and for regional fixed effects.

The IVPROBIT regression is carried out in two steps. Greene (2003) argues that the IVPROBIT approach is more efficient than the standard probit model because it takes into account the correlation between the disturbances u_i and v_i.[14] First,

[14]Moreover, as is the standard probit model, the estimator is consistent event if the normal assumption set of (u_i, v_i) is not true.

Eq. (3.3.2) is estimated as a linear regression to calculate the fitted value of TQ and the residual v. Then, Eq. (3.3.1) is estimated with a probit model using maximum likelihood estimation. In addition to the IVPROBIT model, a standard probit model (PROBIT) is also estimated by treating teacher quality as exogenous (i.e., by replacing TQ with its predicted value). This is done to assess the extent to which the bia caused by unobserved and unmeasured school-specific characteristics plays a role.

3.4 Results

The focus of this paper is on the impact of teacher quality and language of instruction on learning deprivation probabilities of grade 4 primary students in Mauritania and Senegal. I estimate an IVPROBIT model to account for potential endogeneity of the teacher quality variable by using the instrumental variable method. The results of the first stage regression (Eq. (3.3.2)) are in Table **??** while the second-stage results are reported in Table 3.4.1, column 3. A log-likelihood (Hausman (1978)) test was used to examine whether there is a bias caused by unobserved and/or unmeasured school-specific characteristics or if a standard single-equation approach (i.e., PROBIT model) would suffice. The test of the correlation coefficient of the disturbances ($p < 0.01$) suggests that teacher quality is endogenous. Hence, the PROBIT estimator is inconsistent (see Table 3.4.1, bottom). The coefficient ρ (u,v) is different from zero, which suggests that there is a correlation between unobserved factors that drive the average test scores of teachers (teacher quality) and unobserved factors that influence the probability of learning deprivation among students.[15]

The first stage regression, Eq. (3.3.2) includes all the exogenous regressors of the learning deprivation equation (Eq. (3.3.1)) plus the teacher education, the instrumen-

[15] Intuitively, the coefficient ρ (u,v) should be negative but it is not impossible to have a positive sign as I dot not know which unobserved factors influence teacher quality and learning deprivation. For example, there can be a correlation between school management that increases teacher quality and student effort that decreases learning deprivation.

tal variable (IV). Two criteria had to be met to verify the validity of teacher education as an instrument. The first criterion, whether teacher education is correlated with teacher quality, is known in the literature as the relevancy of the instrument. Indeed, research (Stock and Staiger (1997); and Greene (2003) has shown that IV estimates could be highly inefficient if the instruments are weakly correlated with the endogenous variable. The second condition concerns whether the IV is not associated with unobserved factors related to learning deprivation such as, school management (leadership trait of the school principal), physical condition of classrooms, specific teacher characteristics (e.g., teaching method) and specific student characteristics (e.g., self-effort). Otherwise, the assumption that the IV is uncorrelated with the error term of the learning deprivation (Eq. (3.3.1)) would be incorrect. The second condition is more challenging to verify as it cannot be tested statistically when the model is just identified, as is the case here.

Concerning the first criterion, the correlation between teacher quality and teacher education was verified using a single-equation regression (Eq. (3.3.2)) and subsequently using the IVPROBIT model and a Wald test. As shown in table **??**, the coefficient on the teacher education dummy is positive with a value of 4.964 and is statistically significant at the 1 percent significance level. Hence, the first criterion for validity of IV is satisfied. Moreover, a chi-square test (see Greene (2003)) was used to verify whether the teacher education variable is a legitimate instrument. This test is used to assess whether the instrument, in this case, teacher education, is a significant omitted variable from the primary equation (i.e., Eq. (3.3.1)). The results indicate that it does not influence the error term significantly. (See bottom of Table 3.4.1)

Concerning the second condition, the selection of teacher education (i.e., teacher diploma) as the instrumental variable for teacher quality lies essentially on the assumption that teachers graduate from secondary schools with their diplomas before becoming teachers. Getting at least an upper secondary school diploma (baccalaureate) represents an ex-ante measure of teacher quality and is not affected by school-specific factors, unlike teachers performance on the SDI assessment (i.e., test scores), which is measured while the teacher is already on the teaching job in school j. Hence teacher education (i.e., the share of teaches with at least an upper secondary diploma) is truly random and independent of unobserved factors that affect learning deprivation. Based on this argument, the second condition is met, and teacher education is not invalid as an instrument.

At the second stage, based on the estimated parameters of the IVPROBIT model, the marginal effect for teacher quality is -0.0605 and is statistically significant at 10 percent significance level. That is, a decrease in the average teachers score (teacher quality) by one increases the likelihood of a student to be learning deprived by 6.05 percentage points. This result is in line with the literature on the effect of teacher quality on children' s success in school and in adulthood, especially when exposed to quality teaching at young ages. (See Rockoff (2004); Chetty et al. (2017); Buhl-Wiggers et al. (2017)). The marginal effect for language of instruction is 0.980 and is also statistically significant at the 10 percent level. The impact of language of instruction is larger, and the results suggest that learning deprivation for students who are taught in French is 98 percentage points higher than that of students who are taught in a familiar language, i.e., Arabic. In other words, being taught in French increases the probability of being learning deprived. This result is consistent with academic studies on the effect of learning in a familiar language, whereby students are more confident in their learning process when taught in a familiar language (see Brock-Utne (2007) and Trudell and Piper (2013)).

Table 3.4.1: Estimated Marginal Effect of Teacher Quality and Language of Instruction on Student Learning Deprivation Probabilities

	PROBIT		*IVPROBIT*	
	Marg. Ef	Std. Err	Marg. Ef	Std. Err
Teacher quality	-0.0033**	0.0013	-0.0605***	0.0193
Language of instruction	0.447***	0.0655	0.980***	0.185
Student characteristics				
Gender (=1 if Boy)	-0.0228	0.0152	-0.0272	0.0412
Age	-0.0254	0.0423	-0.0843	0.0977
Age2	0.0021	0.0017	0.0060	0.0040
Attended Preschool	-0.0765***	0.0226	-0.151**	0.0637
Attended Koranic school	-0.0404*	0.0214	-0.0878	-0.0561
School characteristics				
Urban	-0.0467	0.0294	-0.182**	0.0819
Public	0.210***	0.0438	0.758***	0.131
Library	-0.0307	-0.0307	0.00494	0.0993
SCR	-0.0039**	0.0018	-0.0073	-0.0053
SCR2	0.00003	0.00002	0.00003	0.00005
STR	0.0020***	0.0007	0.0058***	0.0017
District characteristics				
Poverty rate	0.0316	0.104	0.0273	0.296
% secondary education level	0.0392	0.395	-0.279	1.105
% post-secondary education level	-1.339**	0.672	-1.609	1.916
Region Fixed effects	Yes		Yes	
N	9016		9006	
Log pseudo-likelihood	-58100.3		-441663.5	
Pseudo R2	0.2162		n.a	
$\rho(u, v)$	n.a		0.5156**	
Likelihood-ratio (Hausman) $\rho(u, v)$ =0	n.a		82.93***	
Wald Chi-squared	n.a		1725.11***	

[1] The models are (i) a single-equation probit estimated with control variables, and (ii) an ivprobit estimated with control variables and an instrumental variable. The control variables included in the final tested-down models are student characteristics (Gender, Age, Age squared, Attendance of Preschool, Attendance of Koranic school), school characteristics (urban vs rural; public vs private; and school inputs such as library, SCR, SCR squared, and STR); district-specific characteristics (poverty rate, proportion of population with a secondary education level, and proportion of population with a post-secondary education); and regional fixed effects.

[2] All models are estimated with school-level clustered standard errors, and this table reports the average marginal effects of teacher quality and language of instruction.

[3] The instrument used for teacher quality in the ivprobit model is teacher education.

[4] * $p > 0.10$, **$p > 0.05$ and ***> 0.01

Six of the control variables added to the IVPROBIT regression are statistically significant. As shown on Table 3.4.1, the learning deprivation for a student who has attended preschool is 15.1 percentage points lower than that of a student who has not had preschool education. This result is statistically significant at the 5 percent significant level. It is in line with academic studies of the impact of early childhood stimulation provided by preschool education on child cognitive development. Indeed, early childhood education targeting children ages 3 to 6 can foster foundational skills and boost children's ability to learn (see Currie (2001); World Bank (2018); and Klees (2017)). The student-teacher ratio (STR) at the school level also has a significant impact (though small) on learning deprivation. Learning deprivation of a student in a school with a relatively lower STR (i.e., better learning condition gauged by the adequate number of teachers to teach) is likely to be 0.58 percentage points less likely than for a student who is in a school with a larger STR (i.e., lack of teachers). It is significant at the 1 percent level. I also found evidence of significant gaps in learning deprivation depending on the school location (urban vs rural) and school type (public vs private). Students in public schools are, on average, 75.8 percentage points more likely to be learning deprived compared to their those in private schools. Likewise, students in urban schools are, on average, 18.2 percentage points less likely to be learning deprived than students from rural schools. These results are statistically significant at the 1 percent and 5 percent significance level respectively.

Overall, these results suggest that, after controlling for potential endogeneity and a range of student, school, district related variables and regional fixed effects, both teacher quality and language of instruction have a strong association with learning deprivation. There are data limitations pertaining to the use of the improvement of test scores as the measure of teacher value. Hence, the estimated coefficients represent partial correlation instead of causal impacts.

3.5 Conclusion: Policy Implications, Suggestions for Further Work

In this paper, I estimated the impact of teacher quality and language of instruction on learning deprivation, using a unique primary school-level dataset in Senegal and Mauritania. By using an instrumental variable probit model, I eliminate the endogeneity of teacher quality. Yet, the analysis is constrained by the nature of the dataset as discussed below. Hence, I cannot interpret the results as causal impact. Nonetheless, the results suggest that low-quality teachers are an important reason why primary school students in Senegal and Mauritania are already well behind both the expected curriculum and their peers in other parts of the world after only a few years of schooling. This implies a loss of potential human capital for numerous cohorts of students. I also show that the learning deprivation is higher when a primary student is taught in French versus a familiar language, such as Arabic.

These results also provide some policy considerations for developing countries in Sub Saharan Africa with relatively low learning outcomes. First, reforms that ensure that teachers have greater mastery of the content they teach, could make a big improvement in reducing student learning deprivation. Thus, it would be essential to experiment with different means of improving teacher knowledge. A number of interventions have shown promising results, such as supporting teachers with scripted lesson plans (Banerjee et al. (2017).[16] Second, policy-makers in Sub Saharan Africa countries may be well advised to instruct students in the appropriate language. That is, schools should promote the use of languages that are spoken and understood by teachers and students. In fact, a growing body of research shows that children learn better in their familiar language and comfortably absorb academic content (Hynsj and Damon (2016); and Piper et al. (2016).

[16] See, also, for example, the reviews in Glewwe and Kremer (2006), Evans and Popova (2016), and the discussion in World Bank (2018)

Finally, there are some caveats associated with the analysis in this paper. While this paper uses a unique dataset to estimate the impact of teacher quality and language of instruction, the dataset remains limited, as it is cross-sectional. For example, if students and teachers are assessed several times, it would be possible to control for school fixed effects. Currently, it is not feasible to control for school fixed effects because teacher quality as measured by the average test score of teachers does not vary within a given school. On another note, the complete dataset is available only for Mauritania and Senegal, thus the extent to which the current results could be generalized to other developed countries in SSA remains an open question.

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APPENDIX A

Peer Effects on Academic Achievement: Do Peers Influence Student Effort?

A.1 Uniqueness of the Nash Equilibrium

The GPA equation as a function of effort is given by

$$y_{s,i} = \alpha_s + \delta e_{s,i} + \mathbf{x}'_{s,i}\boldsymbol{\theta} + \eta_{s,i}. \tag{A-1}$$

Students' preferences are characterized by the payoff function

$$u_{s,i}(e_{s,i}, \mathbf{e}_{s,-i}, y_{s,i}) = (c_s + \mathbf{x}'_{s,i}\boldsymbol{\beta} + \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \varepsilon_{s,i})y_{s,i} - \frac{e_{s,i}^2}{2} + \lambda e_{s,i}\mathbf{g}_{s,i}\mathbf{e}_s$$

By replacing the GPA equation in the payoff function, I get a new function denoted $\hat{u}_i(e_i, \mathbf{e}_{-i})$ that does not depend on the GPA. The new utility function is given by

$$\hat{u}_i(e_i, \mathbf{e}_{-i}) = (c_s + \mathbf{x}'_{s,i}\boldsymbol{\beta} + \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \varepsilon_{s,i})(\alpha_s + \delta e_{s,i} + \mathbf{x}'_{s,i}\boldsymbol{\theta} + \eta_{s,i}) - \frac{e_{s,i}^2}{2} + \lambda e_{s,i}\mathbf{g}_{s,i}\mathbf{e}_s. \tag{A-2}$$

The first-order condition of the maximization of $\hat{u}_i(e_i, \mathbf{e}_{-i})$ with respect to the effort e_i gives

$$e_{s,i} = \delta c_s + \lambda \mathbf{g}_{s,i}\mathbf{e}_s + \delta \mathbf{x}'_{s,i}\boldsymbol{\beta} + \delta \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \delta\varepsilon_{s,i}. \tag{A-3}$$

If I write the previous in a matrix form, I get the best response functions of all students at the school level:

$$\mathbf{e}_s = \delta c_s \mathbf{1}_{n_s} + \lambda \mathbf{G}_s\mathbf{e}_s + \delta \mathbf{X}_s\boldsymbol{\beta} + \delta \mathbf{G}_s\mathbf{X}_s\boldsymbol{\gamma} + \delta\boldsymbol{\varepsilon}_s, \tag{A-4}$$

where $\mathbf{1}_n$ is an n-vector of ones and $\boldsymbol{\varepsilon} = (\varepsilon_1, \dots, \varepsilon_n)'$.

Equation (A-4) gives the effort $\mathbf{e}$ as a function of the same variable. This leads to a system of n equations with n unknowns, that has a unique solution iff $||\lambda \mathbf{G}||_\infty < 1$, where the $||.||_\infty$ denotes the infinite norm. As $\mathbf{G}$ is a row-normalized matrix this condition implies that $|\lambda| < 1$.
Moreover, if $|\lambda| < 1$, then $\mathbf{I}_n - \lambda \mathbf{G}$ is a nonsingular matrix, where $\mathbf{I}_n$ is the $n \times n$ identity matrix (see Anselin, 1988). Therefore, the solution of Equation (A-4) is:

$$\mathbf{e}_s = (\mathbf{I}_{n_s} - \lambda \mathbf{G}_s)^{-1}(\delta c_s \mathbf{1}_{n_s} + \delta \mathbf{X}_s \boldsymbol{\beta} + \delta \mathbf{G}_s \mathbf{X}_s \boldsymbol{\gamma} + \delta \boldsymbol{\varepsilon}_s). \tag{A-5}$$

As a result, the game described by the utility function (A-2) has a unique Nash equilibrium given by (A-5).

A.2 Reduced Form Equation of the GPA

My Model

Let $\boldsymbol{\eta}_s = (\eta_{s,1}, \dots, \eta_{s,n_s})'$ be the vector of the idiosyncratic error terms in Equation (A-1). Let also $\mathbf{y}_s = (y_{s,1}, \dots, y_{s,n_s})'$ be the GPAs' vector.
From Equation (A-1), we have $e_{s,i} = (y_{s,i} - \alpha_s - \mathbf{x}'_{s,i}\boldsymbol{\theta} - \eta_{s,i})/\delta$. By replacing this expression of the effort in Equation (A-3), we get

$$\frac{y_{s,i} - \alpha_s - \mathbf{x}'_{s,i}\boldsymbol{\theta} - \eta_{s,i}}{\delta} = \delta c_s + \frac{\lambda \mathbf{g}_{s,i}(\mathbf{y}_s - \alpha_s \mathbf{1}_{n_s} - \mathbf{X}_s \boldsymbol{\theta} - \boldsymbol{\eta}_s)}{\delta} + \delta \mathbf{x}'_{s,i}\boldsymbol{\beta} + \delta \mathbf{g}_{s,i}\mathbf{X}_s \boldsymbol{\gamma} + \delta \varepsilon_{s,i},$$

$$y_{s,i} = \kappa_{s,i} + \lambda \mathbf{g}_{s,i}\mathbf{y}_s + \mathbf{x}'_{s,i}\tilde{\boldsymbol{\beta}} + \mathbf{g}_{s,i}\mathbf{X}_s \tilde{\boldsymbol{\gamma}} + (\boldsymbol{\omega}_{s,i} - \lambda \mathbf{g}_{s,i})\boldsymbol{\eta}_s + \delta^2 \varepsilon_{s,i},$$

where $\kappa_{s,i} = \delta^2 c_s + (1 - \lambda \mathbf{g}_{s,i}\mathbf{1}_{n_s})\alpha_s$, $\tilde{\boldsymbol{\beta}} = \delta^2 \boldsymbol{\beta} + \boldsymbol{\theta}$, $\tilde{\boldsymbol{\gamma}} = \delta^2 \boldsymbol{\gamma} - \lambda \boldsymbol{\theta}$, and $\boldsymbol{\omega}_{s,i}$ is a row-vector of dimension n_s in which all the elements are equal to zero, except the i-th element which is one.

The Standard Model

The standard model reduced form is is similar to equation (1.3.3), where the effort $e_{s,i}$ is replaced by $y_{s,i}$ and the vector of effort $\mathbf{e}$ is replaced by the vector of GPA $\mathbf{y}_s = (y_{s,1}, \ldots, y_{s,n_s})'$. In other words, the standard model is of the form:

$$y_{s,i} = \delta c_s + \lambda \mathbf{g}_{s,i}\mathbf{y}_s + \delta \mathbf{x}'_{s,i}\boldsymbol{\beta} + \delta \mathbf{g}_{s,i}\mathbf{X}_s\boldsymbol{\gamma} + \delta\varepsilon_{s,i} \tag{A-6}$$

Proof of Assumption 1.4.2

I prove assumption 1.4.2 by contradiction. This means that to prove that $\mathbb{E}(\mathbf{G}_s\hat{\mathbf{y}}_s|\hat{\mathbf{X}}_s)$ is not perfectly collinear with the regressors $\hat{\mathbf{X}}_s$ and $\mathbf{G}_s\hat{\mathbf{X}}_s$; I rather start by assuming linear dependence among these independent variables instead. Thus, if $\mathbb{E}(\mathbf{G}_s\hat{\mathbf{y}}_s|\hat{\mathbf{X}}_s)$ is perfectly collinear with $\hat{\mathbf{X}}_s$ and $\mathbf{G}_s\hat{\mathbf{X}}_s$, then I can express $\mathbb{E}(\mathbf{G}_s\hat{\mathbf{y}}_s|\hat{\mathbf{X}}_s)$ as a function of $\hat{\mathbf{X}}_s$ and $\mathbf{G}_s\hat{\mathbf{X}}_s$:

$$\mathbb{E}(\mathbf{G}_s\hat{\mathbf{y}}_s|\hat{\mathbf{X}}_s) = \hat{\mathbf{X}}_s\dot{\boldsymbol{\beta}} + \mathbf{G}_s\hat{\mathbf{X}}_s\dot{\boldsymbol{\gamma}}$$

where $\dot{\boldsymbol{\beta}}$, $\dot{\boldsymbol{\gamma}}$ are unknown parameters. Writing the above equation for a given student i in school s yields the following:

$$\mathbb{E}(\mathbf{g}_{s,i}\mathbf{y}_s - \hat{\bar{y}}_s|\mathbf{G}_s, \mathbf{X}_s) = (\mathbf{x}'_{s,i} - \hat{\mathbf{x}}'_s)\dot{\boldsymbol{\beta}} + (\mathbf{g}_{s,i}\mathbf{X}'_s - \hat{\bar{\mathbf{x}}}'_s)\dot{\boldsymbol{\gamma}} \tag{A-7}$$

where $\hat{\bar{y}}_s$, $\hat{\mathbf{x}}_s$, and $\hat{\bar{\mathbf{x}}}_s$ are the averages of $\mathbf{g}_{s,i}\mathbf{y}_s$, $\mathbf{x}_{s,i}$, and $\mathbf{g}_{s,i}\mathbf{X}_s$ among student who have friends respectively.

Now let's take the specific case of the four students in a school, whose friendship links are described in figure 1.4.1. Taking the previous equation A-7 in difference between students i_1 and i_3 in school s implies :

$$\bar{y}^e_{s,i_1} - \bar{y}^e_{s,i_3} = (\mathbf{x}'_{s,i_1} - \mathbf{x}'_{s,i_3})\dot{\boldsymbol{\beta}} + (\bar{\mathbf{x}}'_{s,i_1} - \bar{\mathbf{x}}'_{s,i_3})\dot{\boldsymbol{\gamma}} \tag{A-8}$$

where $\bar{y}^e_{s,i} = \mathbb{E}(\mathbf{g}_{s,i}\mathbf{y}_s|\mathbf{G}_s, \mathbf{X}_s)$ and $\bar{\mathbf{x}}_{s,i} = \mathbf{g}_{s,i}\mathbf{X}_s$ for all i.

Let assume there is an increase in $\mathbf{x}_{i_2}$ who is separated from i_1 by a link of distance three as shown on figure 1.4.1. As i_3 is i_1's friend, i_2 is also separated from i_3 by a link of distance two. Thus, i_2 is not i_1's friend nor i_3'friend. An increase in $\mathbf{x}_{i_2}$ has no influence on $\mathbf{x}'_{s,i_1}$, $\mathbf{x}'_{s,i_3}$, $\bar{\mathbf{x}}'_{s,i_1}$, and $\bar{\mathbf{x}}'_{s,i_2}$.
In this case, equation (A-8) implies that $\Delta(\bar{y}^e_{s,i_1} - \bar{y}^e_{s,i_3}) = 0$ for any i_3 who is i_1's friend, where the operator Δ measures the variation after the increase in $\mathbf{x}_{i_2}$.

Next, I now show that the above condition $\Delta(\bar{y}^e_{s,i_1} - \bar{y}^e_{s,i_3}) = 0$ or $\Delta\bar{y}^e_{s,i_1} = \Delta\bar{y}^e_{s,i_3}$ is not possible given assumption 1.4.2.

By applying the operator Δ to every term of equation (1.4.8), I have:

$$\Delta\hat{\mathbf{y}}_s = \lambda\mathbf{G}_s(\Delta\hat{\mathbf{y}}_s) + (\Delta\hat{\mathbf{X}}_s)\boldsymbol{\beta} + \mathbf{G}_s(\Delta\hat{\mathbf{X}}_s)\boldsymbol{\gamma}$$

This implies that:

$$\Delta\hat{\mathbf{y}}_s = (\Delta\hat{\mathbf{X}}_s)\boldsymbol{\beta} + \sum_{k=0}^{\infty}\lambda^k\mathbf{G}_s^{k+1}(\Delta\hat{\mathbf{X}}_s)(\lambda\boldsymbol{\beta} + \boldsymbol{\gamma}). \tag{A-9}$$

Equation (A-9) implies that the contextual variables influence on the GPA if an only if $\lambda\boldsymbol{\beta} + \boldsymbol{\gamma} \neq 0$. This is condition (i) of assumption 1.4.2.

Since $\mathbf{x}_l$ increases only where l separated from i_1 by a link of distance three, the i_1-th and j-th rows of $\Delta\mathbf{X}_s$ are zero. Moreover, the i_1-th components of $\mathbf{G}_s(\Delta\mathbf{X}_s)$ and $\mathbf{G}_s^2(\Delta\mathbf{X}_s)$ are zero because no l is i_1's friend and no l is i_1's friend's friend. Thus

:

$$\Delta\bar{y}^e_{s,i_1} = \mathbb{E}(\mathbf{g}_{s,i_1}(\Delta\mathbf{y}_s)|\mathbf{G}_s,\mathbf{X}_s) = \mathbf{g}_{s,i_1}\sum_{k=1}^{\infty}\lambda^k\mathbf{G}_s^{k+1}(\Delta\mathbf{X}_s)(\lambda\boldsymbol{\beta}+\boldsymbol{\gamma}). \tag{A-10}$$

By premultiplying each term of Equation (A-9) by $\lambda\mathbf{G}_s$, we have $\sum_{k=1}^{\infty}\lambda^k\mathbf{G}_s^{k+1}(\Delta\mathbf{X}_s)(\lambda\boldsymbol{\beta}+\boldsymbol{\gamma}) = \lambda\mathbf{G}_s\Delta\mathbf{y}_s - \lambda\mathbf{G}_s(\Delta\mathbf{X}_s)\boldsymbol{\beta}$. By replacing this latter equation in (A-10), I get $\Delta\bar{y}^e_{s,i_1} = \lambda\mathbf{g}_{s,i_1}\mathbf{G}_s\Delta\mathbf{y}_s$ since $\mathbf{g}_{s,i_1}\mathbf{G}_s(\Delta\mathbf{X}_s) = 0$. As $\mathbf{G}_s\Delta\mathbf{y}_s = (\Delta\bar{y}^e_{s,1},\dots,\Delta\bar{y}^e_{s,n_s})'$, the term $\mathbf{g}_{s,i_1}\mathbf{G}_s\Delta\mathbf{y}_s$ if the average of $\Delta\bar{y}^e_{s,j}$ among students j who are i_1's friends; i.e., $\mathbf{g}_{s,i_1}\mathbf{G}_s\Delta\mathbf{y}_s = \Delta\bar{y}^e_{s,i_1}$ since $\Delta\bar{y}^e_{s,j} = \Delta\bar{y}^e_{s,i_1}$ if j is i_1's friend. This is impossible as it implies $\Delta\bar{y}^e_{s,i_1} = \lambda\Delta\bar{y}^e_{s,i_1}$. Indeed, $\lambda \neq 1$ by sssumption 1.3.1 and $\Delta\bar{y}^e_{s,i_1} \neq 0$ because $\lambda\boldsymbol{\beta}+\boldsymbol{\gamma} \neq 0$ (see equation (A-9))

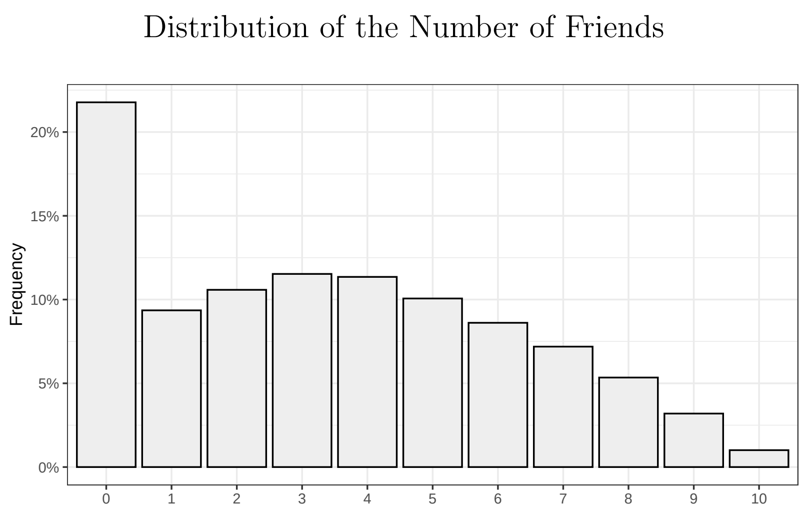
As a result, the mean GPA of peers is linearly independent from the other regressors as far there exists at least one school containing a pair of students separated by a link of distance three. This proves Condition ii of assumption 1.4.2.

Finally, to establish the identification of λ, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$, we set the following condition

Assumption A.2.1. *The matrix* $\tilde{\mathbf{X}}_s = [\mathbf{J}_s\mathbf{X}_s,\ \mathbf{J}_s\mathbf{G}_s\mathbf{X}_s]$ *is full rank.*

Under Assumption A.2.1, since $\mathbb{E}(\mathbf{J}_s\mathbf{G}_s\mathbf{y}_s|\mathbf{G}_s,\mathbf{X}_s)$ is not perfectly collinear with $\mathbf{J}_s\mathbf{X}_s$ and $\mathbf{J}_s\mathbf{G}_s\mathbf{X}_s$, the design matrix of Equation (1.4.7) is full rank. The identification of λ, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ follows.

A.3 Distribution of the Number of Friends



A.4 Description of Variables

Variable Definitions

Variable	Definition
GPA	Average grade in Mathematics, Science, English or Language arts, and History or Social science
Student characteristics	
Age	Age in years
Years in school	Number of years spent in the current school
Female	1 if female; 0 otherwise
(Male)	1 if male; 0 otherwise
(White)	1 if white; 0 otherwise
Black	1 if black; 0 otherwise
Asian	1 if asian; 0 otherwise
Hispanic	1 if hispanic; 0 otherwise
Other race	1 if the race is not in the list above; 0 otherwise
Club member	1 if club member; 0 otherwise
Live with both parents	1 if living with both parents; 0 otherwise
Mother education and job status	
Mother education less than HS	1 if moms education is less than high school; 0 otherwise
(Mother education HS)	1 if moms education is high school; 0 otherwise
Mother education more than HS	1 if moms education is greater than high school; 0 otherwise
Mother education missing	1 if the information about moms education is missing; 0 otherwise
Professional	1 if mom is a doctor, lawyer, scientist, teacher, executive, director, and the like; 0 otherwise
(Stay home)	1 if mom is mom is a homemaker, retired, or does not work; 0 otherwise
Other jobs	1 if moms job is not in the list above; 0 otherwise
Mother job missing	1 if the information about moms job is missing; 0 otherwise

Notes: The variables in brackets are the omitted categories in the following estimations.

APPENDIX B

Do Better Institutions Broaden Access to Sanitation in Sub-Sahara Africa?

B.1 Variables and Data Source

Variables and Data Source

Variable and Definition	Source
Percentage of population with access to improved sanitation facilities	World Development Indicators
Percentage of rural population with access to improved sanitation facilities	World Development Indicators
Percentage of urban population with access to improved sanitation facilities	World Development Indicators
Voice and Accountability	World Governance Indicators
Political Stability	World Governance Indicators
Government Effectiveness	World Governance Indicators
Regulatory Quality	World Governance Indicators
Rule of Law	World Governance Indicators
Control of Corruption	World Governance Indicators
Government Consumption as a share of GDP	World Development Indicators
GDP per capita	World Development Indicators
Age dependency ratio	World Development Indicators
Inflation rate	World Development Indicators
Population density	World Development Indicators
Aid to sanitation as a share of GDP	Authors computation of OECD DAC, WDI data
Foreign direct investment inflows as a share of GDP	World Development Indicators

B.2 Summary Statistics by Country

Summary Statistics of Countries Included in the Empirical Analysis

		Institutional variables						Access to Sanitation		
Courntry	**Code**	**VAE**	**PVE**	**GEE**	**RQE**	**RLE**	**CCE**	**Rural**	**Urban**	**Total**
Angola	AGO	-1.17	-0.55	-1.14	-1.08	-1.31	-1.32	19.23	83.52	44.55
Benin	BEN	0.23	0.34	-0.52	-0.46	-0.55	-0.62	5.93	31.86	16.72
Botswana	BWA	0.52	1.04	0.52	0.56	0.65	0.99	39.37	75.48	59.58
Burkina Faso	BFA	-0.31	-0.22	-0.60	-0.25	-0.43	-0.31	5.90	49.36	16.70
Burundi	BDI	-0.92	-1.63	-1.18	-1.07	-1.15	-1.15	47.29	41.12	46.65
Cabo Verde	CPV	0.93	0.76	0.12	-0.07	0.56	0.89	47.70	76.86	65.92
Cameroon	CMR	-1.02	-0.55	-0.84	-0.84	-1.09	-1.10	26.74	61.45	44.41
Central African	CAF	-1.17	-1.87	-1.52	-1.24	-1.50	-1.13	7.98	39.49	20.23
Chad	TCD	-1.34	-1.48	-1.42	-1.08	-1.43	-1.38	6.15	29.75	11.34
Comoros	COM	-0.41	-0.55	-1.64	-1.40	-0.99	-0.78	26.61	44.29	31.56
Congo, Dem. Rep.	COD	-1.42	-2.15	-1.62	-1.44	-1.61	-1.37	24.82	28.93	26.38
Congo, Rep	COG	-1.09	-0.67	-1.19	-1.23	-1.20	-1.12	5.60	19.10	14.08
Cte d'Ivoire	CIV	-1.00	-1.55	-1.10	-0.82	-1.19	-0.96	9.49	31.75	20.58
Equatorial Guine	GNQ	-1.85	0.06	-1.55	-1.37	-1.36	-1.57	73.87	80.15	76.34
Eritrea	ERI	-2.11	-0.79	-1.21	-1.99	-1.15	-0.40	5.26	48.30	13.66
Eswatini	SWZ	-1.35	-0.23	-0.71	-0.53	-0.60	-0.35	53.84	62.99	55.83
Ethiopia	ETH	-1.31	-1.46	-0.52	-1.05	-0.61	-0.53	25.26	26.60	25.52
Gabon	GAB	-0.86	0.26	-0.76	-0.52	-0.54	-0.83	32.74	42.06	40.70
Gambia	GMB	-1.03	0.06	-0.65	-0.40	-0.46	-0.64	56.33	61.00	58.97
Ghana	GHA	0.40	0.03	-0.08	-0.03	0.01	-0.12	7.72	18.80	13.28
Guinea	GIN	-1.12	-1.42	-1.11	-1.06	-1.37	-1.07	10.32	30.59	17.33
Guinea-Bissau	GNB	-0.86	-0.64	-1.25	-1.12	-1.32	-1.24	7.21	31.62	18.05
Kenya	KEN	-0.23	-1.25	-0.54	-0.24	-0.82	-0.98	28.55	30.25	28.94
Lesotho	LSO	0.02	0.06	-0.42	-0.54	-0.23	0.12	26.17	36.83	28.86
Liberia	LBR	-0.42	-1.01	-1.32	-1.24	-1.06	-0.79	5.08	26.71	15.34
Madagascar	MDG	-0.44	-0.30	-0.81	-0.44	-0.60	-0.43	8.45	17.38	11.25
Mali	MLI	0.06	-0.49	-0.82	-0.47	-0.40	-0.63	14.41	35.90	21.98
Mauritania	MRT	-0.90	-0.58	-0.78	-0.56	-0.83	-0.67	12.28	51.43	34.27
Mauritius	MUS	0.86	0.88	0.82	0.78	0.95	0.39	91.72	93.75	92.56
Mozambique	MOZ	-0.13	0.18	-0.59	-0.48	-0.65	-0.56	8.35	40.62	18.28
Namibia	NAM	0.40	0.83	0.12	0.08	0.17	0.31	15.15	56.02	31.69
Niger	NER	-0.34	-0.79	-0.69	-0.55	-0.59	-0.71	3.92	33.92	9.17
Nigeria	NGA	-0.70	-1.95	-1.03	-0.86	-1.16	-1.15	28.51	34.00	30.89
Rwanda	RWA	-1.25	-0.48	-0.23	-0.34	-0.44	0.13	55.42	59.19	56.11
Senegal	SEN	0.00	-0.19	-0.38	-0.23	-0.21	-0.28	30.72	63.65	44.61
Seychelles	SYS	0.08	0.75	0.20	-0.43	0.08	0.39	98.40	98.40	98.40
Sierra Leone	SLE	-0.28	-0.31	-1.20	-0.91	-0.96	-0.92	6.30	22.48	12.46
South Africa	ZAF	0.62	-0.05	0.48	0.51	0.14	0.20	54.04	68.01	62.57
Sudan	SDN	-1.71	-2.26	-1.31	-1.35	-1.37	-1.31	13.99	44.90	23.54
Tanzania	TZA	-0.24	-0.32	-0.54	-0.42	-0.41	-0.57	7.87	25.30	12.74
Togo	TGO	-1.01	-0.37	-1.39	-0.85	-0.94	-0.95	3.87	24.35	11.48
Uganda	UGA	-0.56	-1.05	-0.51	-0.19	-0.41	-0.91	16.02	28.43	17.76
Zambia	ZBM	-0.14	0.40	-0.59	-0.46	-0.34	-0.36	35.02	55.97	43.35
Zimbabwe	ZWE	-1.47	-0.99	-1.29	-2.00	-1.70	-1.35	31.83	49.90	37.88

Notes: Author's elaboration World Development Indicators and World Governance Indicators. VAE is Voice and Accountability; PVE is Political Stability and Absence of Violence/Terrosim; GEE is Government Effectiveness; RQE is Regulatory Quality; RLE is Rule of Law, and CCE is Control of Corruption.

B.3 Endogenous Institutions - Baseline Results

Baseline Results with Endogenous Institutions

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.953***	0.809***	1.377**	1.578***	1.513**	1.363***	1.609**	5.410***	4.621**
	(0.007)	(0.003)	(0.020)	(0.029)	(0.029)	(0.001)	(0.027)	(0.007)	(0.013)
AIS_{t-1}	1.010***	0.986***	0.966***	0.985***	0.979***	0.987***	0.964***	0.954***	0.963***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	-0.010	-0.004	-0.010	-0.001	-0.008	-0.016	-0.012	-0.006	-0.008
	(0.360)	(0.704)	(0.319)	(0.959)	(0.652)	(0.205)	(0.488)	(0.703)	(0.537)
GDP per capita	-0.026	-0.037	0.263*	-0.132	0.016	0.137	0.150	0.296	0.194
	(0.745)	(0.802)	(0.052)	(0.371)	(0.930)	(0.278)	(0.423)	(0.234)	(0.277)
Age Dependency Ratio	0.017	0.012	0.015	-0.007	0.006	0.026	0.005	0.014	0.011
	(0.340)	(0.384)	(0.399)	(0.665)	(0.767)	(0.103)	(0.831)	(0.677)	(0.673)
Inflation (%)	0.003	0.005	0.003	0.006	0.005	0.002	0.005	0.004	0.003
	(0.306)	(0.176)	(0.264)	(0.231)	(0.370)	(0.584)	(0.230)	(0.321)	(0.456)
Population Density	-0.002	0.001	0.002	-0.001	-0.000	0.001	0.001	0.002	0.002
	(0.143)	(0.151)	(0.323)	(0.631)	(0.823)	(0.579)	(0.501)	(0.395)	(0.312)
Constant	-0.422	0.331	-0.573	3.363	1.559	-1.307	1.119	-3.012	-2.024
	(0.809)	(0.847)	(0.783)	(0.141)	(0.521)	(0.505)	(0.693)	(0.523)	(0.571)
Hansen J test (p-value)	0.984	0.936	0.993	0.895	0.825	0.799	0.994	0.849	0.571
Serial correlation test (p-value)	0.921	0.349	0.355	0.917	0.579	0.541	0.851	0.662	0.938
GMM instruments for levels									
H excluding group	0.635	0.936	0.885	0.947	0.522	0.681	0.902	0.768	0.752
Diff (null H = exogenous)	0.998	0.702	0.985	0.587	0.683	0.730	0.984	0.738	0.918
Instruments for levels equation									
H excluding group	0.871	0.782	0.991	0.690	0.711	0.814	0.979	0.638	0.612
Diff (null H = exogenous)	1.000	1.000	0.681	1.000	0.919	0.418	0.974	1.000	1.000
Observations	513	513	513	513	513	513	513	513	513
Number of countries, N	44	44	44	44	44	44	44	44	44
Number of instruments, i	55	55	55	55	55	55	55	55	55
Instrument ratio, $r = N/i \geq 1$	No	No	No	No	No	No	No	No	No

Notes: p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 1.

B.4 Endogenous Institutions - Foreign Variables

Results with Foreign Variables and Endogenous Institutions

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.976***	0.680***	1.246***	1.310***	1.329***	1.453***	1.471***	4.532***	4.408***
	(0.001)	(0.000)	(0.003)	(0.009)	(0.005)	(0.001)	(0.007)	(0.001)	(0.000)
AIS$_{t-1}$	1.010***	1.011***	0.980***	0.996***	0.988***	0.990***	0.976***	0.981***	0.990***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	-0.000	0.000	-0.007	-0.003	-0.009	-0.017	-0.0105	-0.00586	-0.00296
	(0.993)	(0.993)	(0.460)	(0.856)	(0.546)	(0.109)	(0.415)	(0.684)	(0.844)
GDP per capita	-0.108	-0.202*	0.087	-0.230*	-0.052	0.054	0.0608	0.0266	-0.0429
	(0.299)	(0.098)	(0.538)	(0.091)	(0.698)	(0.661)	(0.695)	(0.865)	(0.752)
Age Dependency Ratio	0.015	0.017*	0.010	-0.004	0.013	0.027	0.0119	0.0156	0.0208
	(0.313)	(0.075)	(0.575)	(0.787)	(0.511)	(0.136)	(0.518)	(0.558)	(0.292)
Inflation (%)	0.004	0.005*	0.002	0.006	0.004	0.002	0.00540	0.00473*	0.00462
	(0.183)	(0.099)	(0.662)	(0.295)	(0.400)	(0.572)	(0.382)	(0.0521)	(0.200)
Population Density	-0.001	-0.001	0.001	-0.001	-0.000	0.000	0.00137	0.000594	0.000416
	(0.413)	(0.437)	(0.721)	(0.346)	(0.931)	(0.984)	(0.408)	(0.731)	(0.807)
Aid to Water and sanitation (% GDP)	-0.040	-0.002	0.041	0.032	-0.026	-0.007	-0.0150	-0.00390	-0.00847
	(0.434)	(0.971)	(0.416)	(0.513)	(0.535)	(0.895)	(0.759)	(0.938)	(0.886)
FDI (% GDP)	-0.002	-0.002	0.001	-0.000	-0.001	-0.002	-0.00319	-0.000549	-0.000708
	(0.280)	(0.237)	(0.187)	(0.909)	(0.815)	(0.183)	(0.230)	(0.833)	(0.734)
Constant	0.132	0.372	0.465	3.345	0.967	-0.773	0.542	-1.853	-2.024
	(0.935)	(0.784)	(0.817)	(0.116)	(0.663)	(0.692)	(0.802)	(0.608)	(0.426)
Hansen J test (p-value)	0.926	0.952	0.939	0.951	0.875	0.633	0.863	0.601	0.519
Serial correlation test (p-value)	0.805	0.521	0.317	0.796	0.680	0.757	0.997	0.927	0.799
GMM instruments for levels									
H excluding group	0.474	0.472	0.551	0.852	0.536	0.778	0.947	0.609	0.419
Diff (null H = exogenous)	0.987	0.996	0.982	0.883	0.932	0.532	1.000	1.000	1.000
Instruments for levels equation									
H excluding group	0.744	0.777	0.624	0.775	0.765	0.206	0.150	0.112	0.120
Diff (null H = exogenous)	1.000	1.000	1.000	1.000	0.897	0.990	0.999	0.998	0.999
Observations	513	513	513	513	513	513	513	513	513
Number of countries, N	44	44	44	44	44	44	44	44	44
Number of instruments, i	57	57	57	57	57	57	57	57	57
Instrument ratio, $r = N/i \geq 1$	No	No	No	No	No	No	No	No	No

Notes: p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 1.

B.5 Regression Results for Rural areas - Baseline

Baseline Results, Rural

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) $\text{Insti}^{(1)}$	(8) $\text{Insti}^{(2)}$	(9) $\text{Insti}^{(3)}$
MIQ, $\hat{\alpha}$	0.119	0.054	0.258*	0.184**	0.232**	0.402***	0.259**	0.889**	0.790**
	(0.169)	(0.473)	(0.075)	(0.020)	(0.026)	(0.001)	(0.019)	(0.019)	(0.019)
AIS_{t-1}	0.994***	0.981***	0.980***	0.984***	0.986***	0.987***	0.986***	0.985***	0.985***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.016**	0.016**	0.013*	0.015*	0.013*	0.004	0.012*	0.012	0.013
	(0.021)	(0.032)	(0.066)	(0.093)	(0.099)	(0.583)	(0.091)	(0.123)	(0.106)
GDP per capita	-0.019	0.068	0.069	0.017	0.026	0.056	0.006	0.023	0.027
	(0.830)	(0.518)	(0.468)	(0.884)	(0.818)	(0.494)	(0.952)	(0.836)	(0.803)
Age Dependency Ratio	-0.005	-0.010	-0.006	-0.010	-0.006	0.001	-0.006	-0.006	-0.006
	(0.393)	(0.152)	(0.302)	(0.148)	(0.330)	(0.875)	(0.317)	(0.327)	(0.301)
Inflation (%)	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.388)	(0.356)	(0.272)	(0.318)	(0.300)	(0.309)	(0.207)	(0.277)	(0.290)
Population Density	0.001	0.002**	0.002**	0.002**	0.001*	0.001*	0.002*	0.002**	0.002*
	(0.456)	(0.045)	(0.037)	(0.039)	(0.096)	(0.071)	(0.051)	(0.049)	(0.064)
Constant	0.643	0.628	0.556	1.028	0.745	0.124	0.837	0.322	0.348
	(0.445)	(0.471)	(0.468)	(0.364)	(0.499)	(0.860)	(0.384)	(0.752)	(0.722)
Hansen J test (p-value)	0.479	0.307	0.463	0.425	0.367	0.503	0.372	0.352	0.360
Serial correlation test (p-value)	0.025	0.035	0.010	0.024	0.031	0.044	0.023	0.022	0.017
GMM instruments for levels									
H excluding group	0.333	0.244	0.205	0.406	0.327	0.325	0.368	0.341	0.316
Diff (null H = exogenous)	0.660	0.492	0.863	0.446	0.462	0.717	0.408	0.413	0.467
Instruments for levels equation									
H excluding group	0.274	0.132	0.293	0.227	0.300	0.435	0.265	0.238	0.209
Diff (null H = exogenous)	0.940	0.977	0.864	0.947	0.570	0.582	0.699	0.731	0.857
Observations	541	541	541	541	541	541	541	541	541
Number of countries, N	44	44	44	44	44	44	44	44	44
No. of instruments, i	42	42	42	42	42	42	42	42	42
Instrument ratio, $r = N/i \geq 1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *p*-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

B.6 Regression Results for Rural areas - Foreign Variables

Results with Foreign Variables, Rural

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.142	0.059	0.271***	0.196**	0.209**	0.409***	0.250***	0.820***	0.742***
	(0.113)	(0.349)	(0.004)	(0.028)	(0.016)	(0.000)	(0.006)	(0.004)	(0.008)
AIS_{t-1}	1.002***	0.993***	0.990***	0.994***	0.996***	0.994***	0.997***	0.995***	0.995***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	0.016**	0.016**	0.012	0.015**	0.014**	0.006	0.0133*	0.0132*	0.0138*
	(0.027)	(0.044)	(0.110)	(0.024)	(0.027)	(0.446)	(0.0509)	(0.0580)	(0.0536)
GDP per capita	-0.065	-0.015	0.007	-0.040	-0.039	0.013	-0.0420	-0.0270	-0.0264
	(0.513)	(0.868)	(0.938)	(0.673)	(0.657)	(0.894)	(0.648)	(0.767)	(0.773)
Age Dependency Ratio	-0.002	-0.006	-0.004	-0.007	-0.003	0.002	-0.00207	-0.00213	-0.00225
	(0.699)	(0.299)	(0.465)	(0.275)	(0.559)	(0.710)	(0.703)	(0.688)	(0.687)
Inflation (%)	0.002	0.002*	0.002	0.002	0.002	0.002	0.00228*	0.00219	0.00210
	(0.225)	(0.056)	(0.138)	(0.125)	(0.141)	(0.191)	(0.0782)	(0.101)	(0.109)
Population Density	-0.000	0.001	0.001	0.001	0.000	0.001	0.000408	0.000570	0.000574
	(0.997)	(0.216)	(0.221)	(0.556)	(0.675)	(0.260)	(0.635)	(0.484)	(0.490)
Aid to Water and sanitation (% GDP)	0.084	0.096	0.101	0.103	0.083	0.072	0.0839	0.0839	0.0853
	(0.217)	(0.243)	(0.273)	(0.238)	(0.273)	(0.261)	(0.266)	(0.265)	(0.257)
FDI (% GDP)	-0.003	-0.002	-0.001	-0.002	-0.002	-0.003	-0.00213	-0.00212	-0.00205
	(0.171)	(0.167)	(0.409)	(0.198)	(0.238)	(0.151)	(0.216)	(0.228)	(0.281)
Constant	0.619	0.688	0.634	1.072	0.733	0.215	0.686	0.204	0.234
	(0.437)	(0.398)	(0.406)	(0.229)	(0.375)	(0.819)	(0.401)	(0.799)	(0.784)
Hansen J test (p-value)	0.275	0.256	0.358	0.262	0.395	0.341	0.366	0.354	0.349
Serial correlation test (p-value)	0.157	0.189	0.132	0.153	0.164	0.128	0.146	0.150	0.149
GMM instruments for levels									
H excluding group	0.578	0.366	0.341	0.469	0.592	0.499	0.531	0.537	0.527
Diff (null H = exogenous)	0.105	0.224	0.424	0.152	0.205	0.219	0.221	0.203	0.205
Instruments for levels equation									
H excluding group	0.203	0.206	0.237	0.117	0.236	0.242	0.226	0.231	0.203
Diff (null H = exogenous)	0.566	0.500	0.690	0.853	0.783	0.631	0.741	0.696	0.768
Observations	513	513	513	513	513	513	513	513	513
Number of countries, N	44	44	44	44	44	44	44	44	44
Number of instruments, i	44	44	44	44	44	44	44	44	44
Instrument ratio, $r = N/i \geq 1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *p*-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

B.7 Regression Results for Urban areas - Baseline

Baseline Results, Urban

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	Insti$^{(1)}$	Insti$^{(2)}$	Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.283**	0.069	0.072	0.192	0.132	0.075	0.164	0.376	0.422
	(0.015)	(0.339)	(0.629)	(0.141)	(0.280)	(0.421)	(0.192)	(0.321)	(0.265)
AIS_{t-1}	1.024***	1.015***	1.017***	1.022***	1.019***	1.016***	1.018***	1.017***	1.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	-0.016	-0.010	-0.009	-0.012	-0.010	-0.009	-0.0106	-0.00971	-0.00959
	(0.222)	(0.340)	(0.526)	(0.268)	(0.328)	(0.383)	(0.311)	(0.361)	(0.352)
GDP per capita	-0.219**	-0.163	-0.167	-0.248*	-0.196	-0.141	-0.188*	-0.179	-0.179
	(0.047)	(0.120)	(0.177)	(0.054)	(0.102)	(0.205)	(0.0791)	(0.109)	(0.106)
Age Dependency Ratio	0.010	0.004	0.005	0.004	0.006	0.006	0.00613	0.00587	0.00610
	(0.122)	(0.367)	(0.336)	(0.395)	(0.304)	(0.212)	(0.244)	(0.254)	(0.246)
Inflation (%)	0.000	-0.000	-0.001	-0.001	-0.001	-0.001	-0.000139	-0.000580	-0.000490
	(0.974)	(0.906)	(0.670)	(0.803)	(0.811)	(0.731)	(0.947)	(0.802)	(0.829)
Population Density	-0.001*	-0.001*	-0.001	-0.001	-0.001	-0.001	-0.00133*	-0.00117	-0.00116
	(0.056)	(0.085)	(0.239)	(0.145)	(0.161)	(0.137)	(0.0890)	(0.118)	(0.119)
Constant	0.404	0.609	0.503	1.093	0.650	0.316	0.623	0.370	0.349
	(0.638)	(0.410)	(0.551)	(0.222)	(0.466)	(0.676)	(0.409)	(0.639)	(0.666)
Hansen J test (p-value)	0.398	0.402	0.338	0.270	0.336	0.403	0.402	0.384	0.363
Serial correlation test (p-value)	0.043	0.059	0.044	0.051	0.072	0.067	0.050	0.050	0.047
GMM instruments for levels									
H excluding group	0.495	0.536	0.331	0.175	0.348	0.255	0.518	0.391	0.416
Diff (null H = exogenous)	0.296	0.261	0.403	0.568	0.375	0.663	0.279	0.398	0.331
Instruments for levels equation									
H excluding group	0.163	0.181	0.183	0.113	0.161	0.178	0.188	0.166	0.150
Diff (null H = exogenous)	1.000	0.993	0.889	0.971	0.952	0.995	0.986	0.995	0.997
Observations	541	541	541	541	541	541			
Number of countries, N	44	44	44	44	44	44	44	44	44
No. of instruments, i	42	42	42	42	42	42	42	42	42
Instrument ratio, $r = N/i \geq 1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

B.8 Regression Results for Urban areas - Foreign Variables

Results with Foreign Variables, Urban

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.254**	0.047	0.054	0.155	0.102	0.011	0.163	0.373	0.420
	(0.011)	(0.462)	(0.717)	(0.358)	(0.447)	(0.933)	(0.258)	(0.424)	(0.387)
AIS_{t-1}	1.024***	1.018***	1.019***	1.020***	1.018***	1.019***	1.018***	1.018***	1.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0)	(0)	(0)
Gov't Expenditure (% GDP)	-0.015	-0.009	-0.010	-0.009	-0.009	-0.009	-0.00957	-0.00957	-0.00892
	(0.124)	(0.444)	(0.361)	(0.427)	(0.442)	(0.433)	(0.396)	(0.395)	(0.399)
GDP per capita	-0.205*	-0.133	-0.137	-0.174	-0.147	-0.131	-0.139	-0.135	-0.132
	(0.072)	(0.207)	(0.251)	(0.210)	(0.248)	(0.181)	(0.207)	(0.263)	(0.254)
Age Dependency Ratio	0.009	0.009	0.008	0.008	0.008	0.008	0.00976	0.00834	0.00977
	(0.108)	(0.171)	(0.255)	(0.160)	(0.155)	(0.297)	(0.135)	(0.224)	(0.166)
Inflation (%)	0.000	-0.000	-0.001	-0.000	-0.001	-0.001	-0.000123	-0.000516	-0.000339
	(0.870)	(0.921)	(0.722)	(0.978)	(0.790)	(0.716)	(0.951)	(0.801)	(0.865)
Population Density	-0.001*	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000890	-0.000926	-0.000858
	(0.090)	(0.288)	(0.193)	(0.139)	(0.186)	(0.272)	(0.264)	(0.173)	(0.275)
Aid to Water and sanitation (% GDP)	0.051	0.100***	0.103**	0.101**	0.091**	0.103**	0.0882**	0.0931**	0.0929**
	(0.161)	(0.009)	(0.010)	(0.014)	(0.025)	(0.013)	(0.0202)	(0.0203)	(0.0218)
FDI (% GDP)	0.001	0.000	0.000	0.001	0.000	0.000	0.000277	0.000481	0.000398
	(0.667)	(0.982)	(0.748)	(0.551)	(0.756)	(0.859)	(0.783)	(0.698)	(0.734)
Constant	0.317	-0.119	-0.050	0.221	0.107	-0.111	-0.0852	-0.199	-0.362
	(0.702)	(0.898)	(0.958)	(0.806)	(0.905)	(0.912)	(0.927)	(0.841)	(0.740)
Hansen J test (p-value)	0.269	0.390	0.367	0.346	0.362	0.329	0.383	0.402	0.379
Serial correlation test (p-value)	0.093	0.134	0.118	0.121	0.143	0.131	0.123	0.124	0.127
GMM instruments for levels									
H excluding group	0.290	0.279	0.265	0.221	0.276	0.232	0.251	0.202	0.175
Diff (null H = exogenous)	0.336	0.592	0.574	0.623	0.542	0.534	0.633	0.774	0.792
Instruments for levels equation									
H excluding group	0.137	0.167	0.145	0.188	0.163	0.142	0.153	0.139	0.135
Diff (null H = exogenous)	0.791	0.944	0.958	0.809	0.911	0.910	0.962	0.992	0.984
Observations	513	513	513	513	513	513	513	513	513
Number of countries, N	44	44	44	44	44	44	44	44	44
Number of instruments, i	44	44	44	44	44	44	44	44	44
Instrument ratio, $r = N/i \geq 1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 2.

B.9 Regression Results for Rural/Urban Gap - Domestic Variables

Results with Domestic Variables, Rural-Urban Gap

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
MIQ, $\hat{\alpha}$	0.657***	-0.557***	-1.062***	-1.171***	-1.351***	-0.750	-1.424***	-4.853***	-4.744***
	(0.006)	(0.006)	(0.000)	(0.002)	(0.005)	(0.259)	(0.000)	(0.000)	(0.001)
Gap^{ur}_{t-1}	1.030***	1.013***	1.000***	1.018***	0.991***	0.968***	1.005***	1.017***	1.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov't Expenditure (% GDP)	-0.019	-0.001	0.009	-0.006	0.005	0.014	0.012	0.014	0.014
	(0.371)	(0.936)	(0.548)	(0.648)	(0.771)	(0.648)	(0.578)	(0.383)	(0.463)
GDP per capita	-0.110	0.159	0.135	0.226	0.359**	0.116	0.274*	0.267*	0.264*
	(0.615)	(0.428)	(0.448)	(0.126)	(0.024)	(0.453)	(0.056)	(0.068)	(0.066)
Age Dependency Ratio	0.005	-0.009	-0.009	-0.004	0.011	0.003	-0.008	-0.009	-0.010
	(0.738)	(0.426)	(0.418)	(0.748)	(0.508)	(0.895)	(0.490)	(0.397)	(0.334)
Inflation (%)	0.004	-0.005	-0.001	-0.003	-0.004	-0.003	-0.004	-0.004	-0.005
	(0.122)	(0.218)	(0.830)	(0.379)	(0.200)	(0.470)	(0.271)	(0.226)	(0.118)
Population Density	-0.000	-0.000	-0.000	0.001	0.001	-0.003*	0.001	0.002	0.001
	(0.959)	(0.841)	(0.998)	(0.570)	(0.645)	(0.071)	(0.796)	(0.455)	(0.599)
Constant	0.351	-0.670	-1.041	-2.147	-4.293**	-0.737	-2.237	-0.135	-0.057
	(0.849)	(0.735)	(0.542)	(0.279)	(0.047)	(0.740)	(0.132)	(0.929)	(0.969)
Hansen J test (p-value)	0.723	0.133	0.716	0.474	0.592	0.837	0.564	0.677	0.632
Serial correlation test (p-value)	0.821	0.608	0.482	0.231	0.251	0.359	0.885	0.605	0.367
Instruments for levels equation									
H excluding group	0.050	0.012	0.511	0.270	0.497	0.778	0.355	0.214	0.300
Diff (null H = exogenous)	0.983	0.587	0.693	0.556	0.557	0.737	0.602	0.821	0.713
Observations	541	541	541	541	541	541	541	541	541
Number of countries, N	44	44	44	44	44	44	44	44	44
Number of instruments, i	39	39	39	39	39	39	39	39	39
Instrument ratio, $r = N/i \geq 1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *p*-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 1.

B.10 Regression Results for Rural/Urban Gap - Foreign Variables

Results with Foreign Variables, Rural-Urban Gap

VARIABLES	(1) Voice	(2) Political	(3) Gov. Eff	(4) Regulation	(5) Rule of Law	(6) Corruption	(7) Insti$^{(1)}$	(8) Insti$^{(2)}$	(9) Insti$^{(3)}$
Gap^{ur}_{t-1}	1.035***	1.034***	1.003***	1.029***	1.007***	0.982***	1.026***	1.035***	1.035***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MIQ, $\hat{\alpha}$	0.832**	-0.156	-1.280***	-0.615	-1.356***	-1.215**	-1.173**	-4.565***	-4.214***
	(0.014)	(0.541)	(0.000)	(0.147)	(0.004)	(0.047)	(0.010)	(0.000)	(0.001)
Gov't Expenditure (% GDP)	-0.043	-0.022	0.009	-0.016	0.011	0.023	0.004	0.005	0.004
	(0.197)	(0.242)	(0.458)	(0.381)	(0.458)	(0.452)	(0.854)	(0.769)	(0.840)
GDP per capita	-0.057	-0.096	0.284	0.059	0.298*	0.164	0.192	0.304	0.289
	(0.867)	(0.529)	(0.103)	(0.606)	(0.071)	(0.477)	(0.277)	(0.108)	(0.152)
Age Dependency Ratio	0.009	-0.004	-0.009	-0.005	-0.001	-0.006	-0.009	-0.011	-0.008
	(0.705)	(0.709)	(0.511)	(0.643)	(0.943)	(0.737)	(0.563)	(0.453)	(0.533)
Inflation (%)	0.004	0.000	-0.001	-0.001	-0.005	-0.002	-0.004	-0.003	-0.003
	(0.334)	(0.928)	(0.692)	(0.856)	(0.160)	(0.744)	(0.246)	(0.342)	(0.329)
Population Density	-0.001	0.001	0.000	0.002	0.002	-0.002	0.002	0.003*	0.002
	(0.740)	(0.163)	(0.894)	(0.148)	(0.527)	(0.358)	(0.217)	(0.090)	(0.122)
Aid to Water and sanitation (% GDP)	-0.091	-0.001	0.042	0.009	0.102	0.056	0.073	0.079	0.080
	(0.380)	(0.992)	(0.308)	(0.772)	(0.239)	(0.519)	(0.210)	(0.211)	(0.186)
FDI (% GDP)	-0.001	0.002	0.001	0.001	0.003	0.002	0.003	0.002	0.002
	(0.776)	(0.671)	(0.816)	(0.743)	(0.419)	(0.683)	(0.583)	(0.651)	(0.767)
Constant	0.123	0.445	-2.114	-0.821	-3.302	-1.026	-1.914	-0.610	-0.816
	(0.969)	(0.713)	(0.257)	(0.602)	(0.144)	(0.661)	(0.397)	(0.771)	(0.693)
Hansen J test (p-value)	0.801	0.139	0.714	0.262	0.437	0.470	0.257	0.441	0.394
Serial correlation test (p-value)	0.903	0.250	0.420	0.162	0.304	0.760	0.473	0.621	0.410
Instruments for levels equation									
H excluding group	0.297	0.274	0.204	0.027	0.123	0.101	0.099	0.147	0.168
Diff (null H = exogenous)	0.840	0.146	0.800	0.570	0.582	0.646	0.389	0.562	0.491
Observations	513	513	513	513	513	513	513	513	513
Number of countries, N	44	44	44	44	44	44	44	44	44
Number of instruments, i	41	41	41	41	41	41	41	41	41
Instrument ratio, $r = N/i \geq 1$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the Hansen J test, the null hypothesis is that the instruments are not correlated with the residuals. For the Serial correlation test is the null hypothesis is that the errors in the first difference regression exhibit no second order serial correlation. For all the regressions we limit the number of lags of dependent variable used in instrumentation to 1.

APPENDIX C

Do Teacher Quality and Language of Instruction Affect Student Learning Deprivation? Evidence from Mauritania and Senegal

C.1 Variable Definitions and Sample Descriptive Statistics

Variable Definitions and Sample Descriptive Statistics

Variable name	Variable description	Mean	SD
Learning deprivation (Dependent Variable)	1 if a student reading score is below the minimum proficiency level and 0 if otherwise	0.52	0.50
Language of instruction	1 if the language used for the language test is French and 0 if it is Arabic	0.89	0.32
Teacher quality	The average test scores of grade 3 and 4 teachers at the school level	43.34	11.25
Teacher education/diploma (instrument)	1 if teacher has at least an upper secondary diploma and 0 if otherwise	0.68	0.27
Boy	1 if student is a boy	0.46	0.50
Age	Student's age (between 10 and 14)	11.73	1.80
Age2	Student's age squared	140.84	43.55
Preschool attendance	1 if student attended a preschool	0.26	0.44
Koranic school attendance	1 if student attended a Koranic school	0.39	0.49
Urban	1 if school is located in an urban area	0.40	0.49
Public	1 if it is a public school	0.84	0.37
Library	1 if school has a reading room	0.09	0.28
Student-classroom ratio (SCR)	The average number of students-per-classroom	36.87	18.97
SCR squared	The average number of students-per-classroom squared	1719.16	1896.13
Student-teacher ratio (STR)	The average student -teacher ratio	43.10	28.81
Poverty rate	Share of population within the district with a daily consumption below the poverty line	0.46	0.21
% of the population with an secondary education level	Share of the population with a secondary education level within the district	0.12	0.07
% of the population with an post-secondary education level	Share of the population with a post-secondary education level within the district	0.02	0.03
Regional fixed effects	A dummy variable for each region	na	na
Observations		N=9,924	

C.2 Sample Descriptive Statistics - Learning Deprived vs Not Learning Deprived Students

Sample Descriptive Statistics

	Learning deprived 1			**Not Learning deprived 2**			**T-test**
	N	Mean	SD	N	Mean	SD	**(1)-(2)**
Age	4.994	11.506	[1.849]	4.747	11.559	[1.763]	0.0520
Gender	5.156	0.463	[0.499]	4.739	0.462	[0.499]	−0.0003
Teacher quality	5.156	39.448	[11.020]	4.739	43.772	[10.775]	4.3240***
Language of instruction	5.156	0.792	[0.405]	4.739	0.912	[0.289]	0.1200***
Attended preschool	5.174	0.208	[0.406]	4.75	0.365	[0.481]	0.1560***
Attended Koranic school	5.174	0.507	[0.500]	4.75	0.360	[0.480]	−0.1480***
Rural	5.174	0.462	[0.499]	4.75	0.604	[0.489]	0.1400***
Public	5.174	0.886	[0.317]	4.75	0.694	[.461]	−0.1920***
Library	5.174	0.067	[0.250]	4.75	0.167	[0.373]	0.1000***
Student-classroom ratio (SCR)	4.877	43.097	[22.340]	4.391	39.161	[19.240]	−3.9360***
Student-teacher ratio (STR)	5.174	52.360	[40.858]	4.75	38.044	[19.791]	−14.3160***
Poverty rate	5.174	0.422	[0.205]	4.75	0.398	[0.227]	−0.0240***
% of the population with a secondary education level	5.174	0.130	[0.074]	4.75	0.151	[0.078]	0.0220***
% of the population with a post-secondary education level	5.174	0.017	[0.026]	4.75	0.031	[0.040]	0.0140***

[1] * $p > 0.10$, ** $p > 0.05$ and *** > 0.01

C.3 Results - Test of Weak Instrumental Variables

Estimated Marginal Effect of Teacher Quality and Language of Instruction on Student Learning Deprivation Probabilities

	PROBIT	
Variables	**Marg. Ef**	**Std. Err**
Teacher education	4.964***	1.346
Language of instruction	-0.117	0.0959
Student characteristics		
Gender (=1 if boy)	0.531**	0.269
Age	0.634	0.0337
Age2	0.0267	0.821
Attended Preschool	0.486	0.483
Attended Koranic school	0.154	0.526
School characteristics		
Urban	-1.243	0.884
Public	5.777***	1.182
Library	1.273	0.990
SCR	0.0524	0.0535
SCR2	-0.0007	0.0005
STR	0.0192	0.0142
District characteristics		
Poverty rate	2.472	3.572
% secondary education level	-11.35	13.72
% post-secondary education level	22.31	18.21
Region Fixed effects		Yes
N		9060
R squared		0.3845

[1] * $p > 0.10$, ** $p > 0.05$ and *** > 0.01

APPENDIX D

D.1 Copyright Permission

15883 Buena Vista Dr. Rockville, MD 20855. United States of America

April 19, 2023

John Nana Francois
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