THE EFFECT OF TUTORING ON SECONDARY STREAMING IN EGYPT

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Abstract

In Egypt, tutoring has developed beyond being a remedial education activity for academically weak students to being an investment tool used by households to enhance children's education performance and give them a competitive edge. Consequently, tutoring represents a sizeable household expenditure, and thus it is important to examine whether, and to what extent, tutoring pays off in terms of better educational outcomes. The literature on tutoring effects is small, and most of it does not take into account the potential endogeneity of tutoring, making the accuracy of the estimated tutoring effect questionable. In this paper, exploiting the longitudinal nature of the dataset, I estimate the effect of taking tutoring on the likelihood of joining the secondary level stream that leads to university. I use the percentage of the working-age population that works in the education sector at the local level—a proxy for the supply of tutors—as an instrument for taking tutoring. Without using an instrumental variable, tutoring has a statistically significant positive effect. After introducing an instrumental variable, this effect disappears, providing some evidence that endogeneity may be present. However, the estimate of the tutoring coefficient is imprecise and there is some evidence that the instrument variable does not have sufficient power to get a reliable estimate of the tutoring effect.

ملخص

نمت الدروس الخصوصية في مصر الى أبعد ما يكون عن أنها نشاط تعليمى علاجي للطلاب الضعيفة أكاديميا إلى كونها أداة استثمار تستخدم من قبل الأسر لتحسين الأداء وتعليم الأطفال ومنحهم ميزة تنافسية. ونتيجة لذلك، فان الدروس الخصوصية تمثل حجم إنفاق كبيرعلى الأسر ، وبالتالي فإنه من المهم دراسة ما إذا كان، وإلى أي مدى، قد تؤتي الدروس الخصوصية بثمارها لايجاد نتائج تعليمية أفضل. ما كتب من أدبيات حول هذه الآثار قليل، ومعظمه لايأخذ في الاعتبار تأثير الجوانب الداخلية المحتملة من الدروس الخصوصية، مما يجعل من دقة قياس التأثير امر مشكوك فيه. في هذه الورقة، وباستغلال طبيعة الطولي للبيانات، قمنا بتقدير أثر تناول الدروس الخصوصية على احتمال الانضمام إلى المستوى الثانوي والذي يؤدي إلى اللحاق بالجامعة. يمكنني استخدام النسبة المئوية من السكان الذين هم في سن العمل والذين يعملون في قطاع التعليم على مستوى وكيل محلي كأداة لاتخاذ الدروس الخصوصية. وفى حالة عدم استخدام متغير جوهري، فان الدروس الخصوصية لها تأثير إيجابي ذات دلالة إحصائية.اما بعد إدخال متغير جوهري، يختفي هذا التأثير، وتتوافر بعض الأدلة على أن الجوانب الداخلية قد تكون موجودة. ومع ذلك، فإن تقديرات معامل التدريس غير دقيقة، وهناك بعض الأدلة على أن المتغير أداة ولا يملك طاقة كافية للحصول على تقدير موثوق لتأثير الدروس الخصوصية.

1. Motivation

Households in Egypt, like many developing countries, spend substantially on tutoring. According to the World Bank (2002), aggregate household spending on tutoring at the pre-university level represents the largest household education expense (even compared to spending on private school tuition and fees). According to the Economist Intelligence Unit (1996), it is not uncommon for households with children in the secondary level of education to spend up to 25% of annual income on tutoring. Observing so many parents deciding to invest in tutoring does not necessarily imply that there are corresponding high returns to tutoring. There may be imperfect information on payoffs, especially given that some of the returns are long term, and that parents' decisions may be affected by peer effects rather than by information on payoffs. It is therefore important to find out if such an investment pays off in terms of better education outcomes or if these resources would be better spent on improving the quality of the formal schooling system. This paper, therefore, fits in the larger literature on the effectiveness of public versus private educational investment on education achievement and outcomes.

This increased importance of tutoring as a crucial form of educational investment in many developing countries can have equity implications, since wealthier households are more likely to afford tutoring (or higher-quality tutoring, in settings where tutoring is nearly universal). Income inequality can be exacerbated as students from richer backgrounds may get better education outcomes, and therefore better future labor outcomes, as a result of their participation in tutoring. The literature on tutoring determinants confirms that socioeconomic status, represented by variables such as household income and parental education, is consistently a strong predictor of taking tutoring [Stevenson and Baker (1992), Buchmann (2002), and Tansel and Bircan (2005a)]. A similar finding holds in the case of Egypt, where it was found in Elbadawy et al. (2006), that children in wealthier households are significantly more likely to receive private tutoring. Examining if tutoring really improves education outcomes is one step towards assessing the equity implications of tutoring.

The literature on tutoring effectiveness is still in its infancy and its results are mixed. More importantly, most of the literature does not take into account that tutoring may be endogenous. Unobserved characteristics such as academic ability and household appreciation of education can be linked to both tutoring and education outcomes. This can cause the estimates of the tutoring impact on education outcomes to be biased.

This paper assesses the effect of taking private tutoring on which secondary (high-school) stream a student joins in Egypt. The panel nature of the dataset allows me to have information on the tutoring status of students in 1998 and their education outcomes as observed in 2006. I use the percentage of the population working in the education sector at the local level as an instrument for tutoring to overcome the problem of endogeneity.

The remainder of this paper is organized as follows. The next section reviews the literature looking at tutoring effects. The third section provides information on the dataset used and a discussion of the adopted methodology. The results are presented in the fourth section and conclusions follow in the last section.

2. Background

2.1 Tutoring effects

One possible beneficial effect of tutoring is that it can be remedial. It provides weaker students with access to teaching tailored to their level (de Silva 1994). It can also be a necessary learning supplement in the case of low-quality schooling. Even though the direct effect of tutoring on student achievement is expected to be positive, tutoring benefits may be partially offset by a reduction in student study productivity and a reduction in school attendance. When pupils spend substantial time in tutoring classes after long school days, they are deprived of recreational time and may suffer a reduction in sleeping hours, leading to increased stress and fatigue (de Silva 1994, Fenech and Spiteri 1999, Wijetunge 1994, as cited in Bray 1999/ 2003). In addition, as their afternoons and evenings are reserved for tutoring, many students need to take days off school in order to study. In other words, tutoring may affect school attendance (Hussein 1987, de Silva 1994) and can become a substitute for education at school. It is also important to note that while tutoring is expected to have positive impacts on test scores, as it is predominantly an exam-preparation activity in developing countries, its effects on cognitive achievement are unclear.

Tutoring can have implications on other students and on the education system as a whole beyond its effects on students receiving it. Bray (2003) presents a discussion of the effects of tutoring on mainstream schools. For example, students taking tutoring may cause disruption to teaching in school as they are not as in need of in-class teaching. Moreover, when tutoring is widespread, school teachers may compromise on the quality of teaching they provide because of an expectation that their students already receive tutoring. This has a reinforcing effect as students who initially were not planning to get tutoring are led to do so. Furthermore, in settings where tutors are primarily school teachers, as is the case in Egypt, spending extended hours in tutoring activities leaves less time for teachers to prepare for their school classes and, more importantly, less time for professional development (Dessy et al. 1998, Hussein 1987).

As pointed out in the previous section, tutoring may also have important equity implications, as it may be more affordable to children belonging to richer households. Moreover, for poor households that are already resource-constrained, tutoring can affect the enrollment and dropout decisions of their children given that it represents a substantial education cost.

Despite the recognition of tutoring impacts beyond the direct impact on an individual, I will only be able examine direct impacts on educational outcomes due to data limitations. This is also the case in the literature, where the focus has generally been on its effect on short-term academic performance as reflected in test scores.

2.2 Evidence on tutoring effectiveness

The focus in the literature has been on the effect of tutoring on academic performance as measured by scores, and less often, as measured by the likelihood of being admitted into university (e.g. Papas and Psacharopoulos 1987, Stevenson and Baker 1992, and Tansel and Bircan 2005b). The evidence was initially based on simple bivariate correlations between tutoring and scores (e.g. Kulpoo 1998 and Paviot et al. 2005). It evolved into using multivariate statistical methods such as linear regression to control for child, household, and school factors. The direction of the effect of tutoring in that work is varied. For example, Kulpoo (1998), Buchmann (2002), and Tansel and Bircan (2005b) found tutoring to have a positive effect[1]. In other papers, the effect of tutoring was significant and positive in some but not all tests, tutoring types, or countries analyzed (e.g. Stevenson and Baker 1992, Fergany 1994, Paviot et al. 2005, Ireson and Rushforth 2005, and Ha and Harpham 2005)[2]. Others

[1] Kulpoo (1998) found a positive correlation between private tuition and reading and literacy levels in Mauritius. Buchmann (2002) found tutoring to have a positive and significant effect on self-reported academic performance and a negative and significant effect on grade repetition in Kenya. Tansel and Bircan (2005b) found, using OLS regressions, that tutoring had a strong positive effect on scores obtained in the university entrance examination in Turkey.

[2] Stevenson and Baker (1992) found that using practice examinations and correspondence courses while in high school in Japan increased the likelihood of attending university. Attending an after-school class does not have an effect, and hiring a tutor has a negative but insignificant effect. Fergany (1994) found that while private and group tutoring at the primary and preparatory education levels in Egypt increases the chances for completion of the primary education level, they have no significant impact on achievement as measured by scores. Paviot et al. (2005) found that the average reading and mathematics scores are higher for pupils taking tutoring in four African countries (Malawi, Mauritius, Zambia and Zanzibar) and lower in two African countries (Namibia and Kenya). Ireson and Rushforth (2005) found that tutoring has a positive effect on average GCSE scores in the UK only for non-white students while for white students, the coefficients were insignificant. Tutoring in mathematics had a significant effect on the mathematics score while that in English had an insignificant

found tutoring to have an insignificant effect (Papas and Psacharopoulos 1987, Baker et al. 2001, Lee et al. 2004) or even a negative effect (Cheo and Quah 2005)[3].

The main issue with the papers above is that they do not take into account the endogeneity of tutoring in estimating its effect. Therefore, the estimates of the tutoring effect are unreliable. Innate academic ability and parents' preference for education represent two sources of endogeneity. Unobserved innate academic ability can affect the tutoring decision. Weaker students may be more likely to need tutoring as a remedial education supplement. The tutoring effect can therefore be underestimated when innate ability is not observed. In contrast to that scenario where parents invest in tutoring to compensate for a child's weak ability, parents may choose to invest in tutoring in their most academically promising child, thereby reinforcing academic ability differences. It may also be that children who are more motivated also are more likely to demand tutoring services. Under that event, the tutoring effect would be overestimated since strong academic ability and motivation are not observed and their effects on education outcomes will be attributed to tutoring instead. Additionally, factors such as the value parents place on their children's education is another channel through which a bias in the tutoring effect can result. Since this is again an unobserved variable, the tutoring variable can pick up its effect thereby resulting in an overestimated tutoring effect.

Endogeneity is essentially a self-selection issue: students do not randomly select into tutoring. They select into tutoring based on the unobservable characteristics discussed above. Accordingly, the endogeneity problem does not arise in a random experiment where students are randomly assigned into tutoring. A few papers relied on such experiments to estimate the effect of tutoring (e.g. Haag 2001; Mischo and Haag 2002). They found that those assigned into tutoring in Germany had better scores than students of similar academic level. As pointed out in Dang and Rogers (2008), what is estimated in such experiments is the effect of being assigned to receive free tutoring and not the effect of the household deciding to purchase tutoring services.

The work cited above, except for those using random experiments, did not deal with the issue of endogeneity and mostly did not acknowledge it. Some of the papers controlled for previous achievement, e.g., previous scores, which may be correlated with innate ability. Also, many in that body of work controlled for parents education and/or household income, which may be correlated with parents' concern about their children's education[4]. However, this would at best only partly capture the unobserved variables' effects, and therefore would not fully overcome the bias created by endogeneity. Also, previous achievement may also be endogenous if it is affected by prior tutoring activities.

It was only very recently that attempts were made to estimate the impact of tutoring while accounting for its endogenous nature (Suryadarma et al. 2006, Dang 2007, Kang 2007a). These papers used an instrumental variable approach where a variable that directly affects the tutoring decision, but does not directly affect education outcomes, is used to instrument for tutoring. The tutoring effect in the literature taking into account endogeneity is also mixed. Suryadarma et al. (2006) uses the proportion of classmates taking tutoring as an instrument in

effect on the English score. Ha and Harpham (2005) found that tutoring in Vietnam has a positive effect on reading test scores and an insignificant effect on writing and multiplication test scores.

[3] Papas & Psacharopoulos (1987) found that tutoring did not play a significant role in the likelihood to go to university. However, they included high school grade as a regressor and they suggest that the lack of the tutoring effect may be because its effect is captured by the high school grade. Baker et al. (2001) used cross-national data from the Third International Mathematics and Science Study (TIMSS). They found that national indicators of tutoring use had no significant effect on the national mean math scores. Lee et al. (2004) focused on tutoring taking place before the school year starts in Korea. They found that tutoring hardly helped in getting higher grades. Cheo and Quah (2005) found a negative link between the time spent with a tutor and scores in high-tier schools in Singapore.

[4] Also, Cheo and Quah (2005) limited the analysis to students in high-level schools in Singapore, where selection into schools is based on academic ability reflected by scores. So, in a way, academic ability is controlled for.

his analysis of tutoring effects on scores in Indonesia. It was found that tutoring has no significant effect on scores.

Dang (2007) exploits a government policy in Vietnam whereby fees that can be charged for tutoring services are specified. He uses the fees charged by schools at the community level to instrument for spending on tutoring. He uses a joint Tobit and ordered probit model. He finds tutoring to have a significantly positive effect on student academic performance. It is not clear how tutoring fees vary with tutoring quality which would affect the measurement of the tutoring impact.

Kang (2007a) uses birth order as an instrument for tutoring spending in South Korea. This is on the basis that parents may make different educational investments for different children (e.g., they may favor their first-born). Kang recognizes that this instrument has the weakness that if parents favor a particular child in tutoring investments, they are likely to also favor that child in other investments that are not captured in the data; e.g., parents may provide study help themselves. Therefore, the instrument can affect educational performance via other channels in addition to tutoring and the tutoring effect may therefore be overestimated. However, Kang finds tutoring to have an insignificant effect making the bias issue of no concern[5]. Among the interpretations he gives for his finding is that tutors may be providing low-quality services. Also, parents' investments may be driven by peer effects rather than real tutoring returns.

3. Data and Methodology

3.1 Data

In this paper, I employ the Egypt Labor Market Survey of 1998 (ELMS 98) and the Egypt Labor Market Panel Survey of 2006 (ELMPS 06). The ELMPS 06 is the first longitudinal survey in Egypt. It follows the ELMS 98. Both are nationally representative surveys. Approximately 72% of the individuals interviewed in 1998 were successfully re-interviewed in 2006, forming a panel that can be used for longitudinal analysis. I exploit the longitudinal nature of the data in examining the effects of taking private tutoring on the secondary branch in which an individual is streamed[6]. I use tutoring information based on ELMS 98 for those who were students in the preparatory level (before secondary streaming) in 1998[7]. The secondary stream that an individual has joined is identifiable using ELMPS 06, whether or not the individual is still a student[8].

ELMPS 06 also contains retrospective questions on the education experience of an individual that were not included in ELMS 98. I use these to derive extra information corresponding to the education experience of individuals in my sample prior to and during 1998. For example, information about school characteristics (such as frequency of computer use, degree of reliance on corporal punishment at school, and whether the school operated in multiple shifts) was collected for schools attended in the primary, preparatory and secondary levels[9]. In addition, ELMPS 06 contains information on grade repetition that took place in each of the three pre-university education levels.

Pre-university education in Egypt consists of three education levels: the primary, preparatory and secondary levels. After the end of the preparatory level, education branches off into two

[5]Kang's results are robust. He checked for heterogeneous effects by sex, pre-tutoring ability and family income and found the lack of tutoring effect to still hold. He also found tutoring to be insignificant using a non-parametric bounding method (Kang 2007b).

[6] I do not look at the effect on university outcomes because the field/discipline joined at the university level is only identifiable for university graduates and not for university students, thereby resulting in a small sample that may generate unreliable estimates if an instrument variable estimation procedure is used. In addition, there are some methodological issues with the construction of a university rank variable particularly that there is no information on the university from which an individual has graduated.

[7] For information on tutoring patterns based on ELMS 98, please refer to Elbadawy et al. (2006).

[8] ELMPS 06 does not have information on scores obtained in standardized tests held at the end of each education level.

[9] ELMS 98 has information on whether the school operated in multiple shifts only for the school attended in the primary level.

secondary-level streams: general and vocational. Admission into streams depends solely on the score obtained in the standardized examination held in the final grade of the preparatory level[10]. The general secondary stream requires a higher score in the preparatory diploma. It is an academic stream and is regarded as the "prestigious" stream as it leads to university. The vocational stream is mainly a terminal degree[11]. Based on ELMPS 06, the breakdown of the general secondary track graduates whose age is below or equal to 30 is such that 3% do not continue to higher education, 88% go to university and 9% go to above intermediate institutes[12]. As for the technical track graduates: 87% do not proceed to higher education while 6% join university and 7% join above intermediate institutes. Some 95% of those who were admitted to universities (aged 30 or below) attended the general track. Therefore, looking at which branch a student joins at the secondary level is essentially like looking at whether or not they will join university.

I restrict the sample I use in the analysis to those who (1) were preparatory students in 1998 and (2) based on ELMPS 06, have progressed in the education system to the point of having to go into one of the secondary streams (i.e., either students in the secondary level or higher or graduates whose highest education level is secondary or above[13]. The sample contains 1,116 observations.

The sample captures students at different grades in the preparatory level in 1998. The tutoring question applies to their grade in 1998 and not to the final (third) grade in the preparatory level. This creates an asymmetry where if a student took tutoring in the first or second (less critical) grades in 1998, it is likely that he/she also took tutoring in the more critical third grade. However, a student not receiving tutoring in the first and second grade does not necessarily mean they did not take tutoring in the third grade. This can potentially create a bias in the estimate of the tutoring effect. On one hand, assuming a tutoring has a positive effect on scores, we can observe cases which in reality were tutored in the third grade and that helped them get a higher score but because they were observed in the first or second grade when they did not get tutored, the tutoring effect in their case will be underestimated. On the other hand, it may be the case that those who took tutoring in the first and second year were more likely to be weak students or were more likely to belong to families that are keener on education outcomes. Also, the tutoring effect for the students who took tutoring in the first and second year may be higher, if they will also be tutored in the third year, because of a cumulative tutoring effect. Therefore, the tutoring effect for those taking tutoring in the first and second grades may be over or underestimated.

3.2 Methodology

As explained above, two countervailing sources of non-random selection into tutoring may occur. One source of bias derives from the selection of academically weak students into tutoring. The other derives from the selection of children that are more motivated or that belong to households that are more appreciative of education.

The two sources of selection have opposing effects. Thus, the direction and magnitude of bias in the OLS models is unknown, and depends on the relative effect, as well as the importance of these factors in determining students' outcomes. Least squares estimates of the private tutoring effect will be biased if tutoring is correlated with unobserved factors that determine performance on the preparatory diploma examination and hence on the secondary tracking

[10] This examination is standardized at the governorate level.

[11] It is possible for graduates of the vocational track to join university if their scores on the standardized exam held at the final year are higher than a particular cutoff, in which case they can only join a university field related to their vocational specialization. However, this does not occur frequently.

[12] Above intermediate institutes are similar to 2-year colleges.

[13] The sample excludes those who did not continue education beyond the preparatory level, since they left the system without joining either streams.

outcome. I expect both sources of bias to exist in the case of Egypt. However, given the prevalence of tutoring in Egypt, it appears to be more of an investment than a remedial educational activity. If endogeneity is not properly controlled for, I expect that the tutoring effect obtained will be overestimated and hence should be treated as an upper-limit estimate subject to its standard error.

To address concerns regarding bias due to non-random sorting of students into tutoring, I use an instrumental variable approach,

$$\Pr(Y_i = 1 \mid X_i, Z_i) = \Pr(\alpha_0 + \alpha_1 X_i + \alpha_2 Z_i + \varepsilon_i < 0) \qquad (1)$$

$$\Pr(Z_i = 1 \mid X_i, IV) = \Pr(\beta_1 + \beta_2 X_i + \beta_3 IV_i + \delta_i < 0) \qquad (2)$$

for all $i = 1,2,...n$ individuals. Y is the binary dependent (outcome) variable taking a value equal to zero if a student joins the vocational stream and a value equal to one if a student joins the general stream. Y depends on a vector of characteristics (X) and the private tutoring binary variable (Z) which takes the value zero if the student did not take tutoring in 1998 and one if he/she did take tutoring. Endogeneity is reflected in Z and ε potentially being correlated. To overcome endogeneity, equation (2) is used where IV is an instrument variable for tutoring and the error terms (ε and δ) are allowed to be correlated.

I employ a measure of the local availability of potential tutors as an instrument for participation in tutoring[14]. In particular, I use as an instrument the percentage of the working age population that work in the education sector at the local level (village/*shyakha*), based on data from the Census of Egypt in 1996. Since both the dependent and the tutoring variables are binary, I use an IV probit estimation. I also run probit estimation to get the results without accounting for endogeneity.

The limitation of the instrument I use is that those working in the education sector include not only teaching staff but also administrative staff. In addition, the measure includes those working in the education sector and which are *residing* in the same locality as the student, and not necessarily where they work. However, this issue may be alleviated since they may give tutoring in the locality where they reside rather than the locality where they work.

The vector of independent variables (X) consists of student, household, preparatory school, and regional characteristics[15]. Child characteristics include: age in 1998, squared-age in 1998, sex, ever-repeating a grade in the primary level, and being the eldest child in the 1998 household[16]. The age variables are meant to help in reducing the bias caused by the fact that students are observed in different grades in the sample. They can also help in capturing a cohort effect resulting from students in different grades experiencing the outcome: secondary streaming in different periods. Grade repetition in the primary level should proxy for past weak achievement[17].

The household characteristics consist of father's and mother's education, household wealth in 1998, and father's and mother's presence in the household in 1998. Education is represented by a group of dummy variables, each denoting a given level of education attainment: illiterate, reads and writes, less than intermediate, intermediate, above intermediate and

[14] Tutors in Egypt are more likely to be school teachers.

[15] Table 1 provides mean and standard deviation of these variables for the sample used in the analysis.

[16] The eldest child variable indicates that a student is the oldest child (son or daughter) of the household head that was present in the household in 1998. Therefore, a student will be considered the eldest if he/she had older siblings that moved out of the household before 1998. The eldest child is constructed using the 1998 data because this was the time the tutoring decision was made and in 2006, the student may have moved out of the parental household making it impossible to know if he/she was the eldest child.

[17] Only 3% in the preparatory level repeated grades while in the primary level.

university and above[18]. Each dummy is set to equal one if the education level attained is equal to or exceeds a given level of education. This configuration is followed in order to reflect the incremental effect of each education level compared to its previous level. The illiterate or above group is the omitted group. A wealth score is constructed using factor analysis based on household asset ownership and house characteristics information. Based on the score, households are divided into five quintiles[19]. The omitted category is the lowest wealth quintile.

The preparatory school quality controls are very important. Even though these correspond to the schooling experience in 1998, the information was actually collected in ELMPS 06 as mentioned above. These controls are: whether the preparatory school operated in shifts (i.e., multiple school sessions); the computer use frequency in the school; and whether corporal punishment was used. The schools operating in multiple sessions are generally thought to be of less quality because each school session tends to be shorter than the school session in a single-shift school. The computer use and the corporal punishment variables reflect school quality as computer use reflects the state of physical facilities and corporal punishment reflects negative teaching practices.

Community variables used are the teacher-pupil ratio at the governorate level in the school-year 1997/1998 and the region where the student resided in 1998. The regional categorization incorporates an urban/rural breakdown[20]. The Greater Cairo region is the omitted category. The regional dummies can capture differences in the schooling side or in the tutoring demand side.

4. Results

4.1 Tutoring effect

Estimation results are provided in table 2 and 3[21]. The probit model estimates (table 2), in which endogeneity is not taken into account, are listed in column 1. The IV probit results are in column 2 and 3 which report the coefficient estimates from equations (1) and (2), respectively (as presented in Section 3.2). It can be seen that, without taking endogeneity into account (column 1), receiving tutoring in the preparatory level significantly increases the probability of joining the general stream at the secondary level. However, upon using the instrument variable approach, tutoring becomes insignificant (column 2). This may reflect that, as pointed out earlier, the tutoring effect bias in the case of Egypt is expected to be upward. Therefore, upon controlling for endogeneity, the tutoring effect is reduced. However, the coefficient is imprecisely estimated (note the larger standard error on the tutoring coefficient in column 2). This suggests that even though the instrument is significant in the first-stage probit (column 3), it may not be powerful enough to identify the tutoring effect.

I used the test of exogeneity introduced by Smith and Blundell (1986)[22]. Under the null hypothesis, the tutoring indicator is exogenous. The residuals from the tutoring equation, using the instrumental approach, are used as an additional regressor. If the null-hypothesis holds, the residuals should have no explanatory power. The p-value for the test was 0.9235.

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[18] I follow the education categories used by the Central Agency for Public Mobilization and Statistics CAPMAS. The "reads and writes" category denotes someone who can read and write but who does not have any diploma. Intermediate education means secondary (high-school) level education. Therefore the less than intermediate category means those with a primary or preparatory degree. The "intermediate" category denotes someone with a secondary diploma. The "above intermediate" category denotes those who graduated from an above-intermediate institute (similar to a 2-year college).

[19] See Filmer and Pritchett (2001) for the factor analysis methodology used to construct the wealth score.

[20] The regional breakdown used in this paper is as follows: Greater Cairo, Alexandria and Suez Canal governorates, Urban Lower Egypt, Rural Lower Egypt, Urban Upper Egypt and Rural Upper Egypt.

[21] I used STATA in the estimation as well as in the generation of descriptive statistics.

[22] This is implemented using the "probexog" user-written routine in STATA. It was created by Christopher F. Baum.

Therefore, the null-hypothesis that tutoring is exogenous cannot be rejected[23]. One issue to take into consideration is that the exogeneity test hinges on the validity of the instrument. If the instrument is not a strong enough predictor in the tutoring equation, the standard errors are large making the test fail to reject the null-hypothesis of exogeneity. This makes it unclear if the result of a positive tutoring effect based on the probit model is more appropriate than the result of an insignificant tutoring effect based on the IV-probit.

In an attempt to see if the large standard errors of the tutoring estimate resulted from using a non-linear instrumental model instead of a linear instrumental model, I compare the two-stage least squares (2SLS) estimates (table 3) to the IV-probit estimates (table 2). In addition, ordinary least squares (OLS) estimates are given (table 3, column 1) to see how the standard errors of the tutoring estimate compare to those in the 2SLS model, which instruments for tutoring. While the variables of interest are binary, making an IV-probit model appear suitable for analysis, the use of 2SLS is not improper. Angrist (2001) argues that as long as the purpose of estimation is the identification of the causal effect of treatment, 2SLS can be used as an estimation strategy when dealing with limited dependent variables. Even if the actual second-stage relationship is nonlinear, 2SLS is useful as it captures an effect similar to a local average treatment effect (LATE) (Angrist and Imbens 1995; Heckman and Vytlacil 1998).

Comparing results in the linear models to the non-linear ones (OLS to probit and 2SLS to IV-probit) shows that while the coefficient sizes are smaller in absolute terms in the linear models, the sign of the coefficients and their statistical significance levels are generally the same. The large increase in the standard errors of the tutoring effect does not appear to be a result of using a non-linear model but rather a result of using an instrumental approach; the standard errors go up considerably when going from an OLS to a 2SLS model (table 3) and from a probit to an IV-probit model (table 2).

It is recognized in the literature that the standard errors in instrumental variable models are much larger if the instrumental variable is only weakly correlated with the endogenous regressors. Despite the IV variable turning out to be significant at the 5% level in the first stage (tutoring) equation in both the IV-probit and 2SLS, it may not be strong enough to explain a lot of variation in tutoring. Therefore, since both estimators correct for endogeneity using fitted values, efficiency is lost resulting in large standard errors. Therefore, formal tests of IV weakness were employed following the 2SLS estimation (as such tests are currently not available for non-linear model in STATA)[24].

The test of the weakness of instruments is based on the Cragg Donald minimum eigenvalue statistic created by Cragg and Donald (1993). The value of the statistic is compared to critical values in table 2 of Stock and Yogo (2005). This test uses an F-statistic to test the hypothesis that the coefficients on the instrument equals zero in the structural equation. The test statistic value is 5.033 (below the threshold of 10 suggested by Staiger and Stock (1997) and which is often used in the literature). Comparing the value of the test statistic to the critical values leads in the acceptance of the null hypothesis that the instrument is weak, because the statistic is smaller than the critical values even up to a rejection rate of 25% of a Wald test with a nominal size of 5%[25]. A weak instrument reduces the power of the exogeneity test. Therefore, a better instrument is needed, not only to get more reliable results, but also to construct a more powerful exogeneity test.

[23] Exogeneity of the tutoring variable was also not rejected based on the Wald test of exogeneity provided by STATA with the "ivprobit" command.

[24] In particular, the tests are obtained using the "estat firstage" command after running an "ivregress" (2SLS) command in STATA.

[25] The 2SLS size of nominal 5% Wald test is 16.38, 8.96, 6.66 and 5.53 for the rejection rates of 5%, 15%, 20% and 30% respectively. For more details, refer to Stock and Yogo (2005).

A recent literature has emerged in which parameter tests and confidence sets that are robust to weak instruments were developed. Among these is the Conditional Likelihood Ratio (CLR) test introduced by Moreira (2003). The basic idea is to construct correct significance levels that overcome the size distortions resulting from weak instruments by using critical values for likelihood ratio tests that are conditioned rather than constant, i.e., values that are based on the conditional distribution of nonpivotal statistics. Given the acceptance of the hypothesis that the instrument is weak, I used the "condivreg" command in STATA to conduct the CLR and the corresponding confidence sets[26]. The coverage-corrected confidence set based on CLR is [-2.020407, 1.295237] (the tutoring coefficient p-value is still 0.963)[27]. This is compared to a confidence set associated with the 2SLS [-0.7953941, 0.7579207]. As expected, the corrected confidence interval is wider[28].

4.2 Other variables

Focusing now on the probit and IV-probit estimates in table 2, the results for the secondary streaming outcome equation (columns 1 and 2) indicate that grade repetition in the primary level has a significantly negative effect on joining the general stream, which is reasonable since that stream requires higher test scores. Father's education, especially the intermediate education level, and household wealth are positively linked to joining the secondary stream. Father's presence has a negative effect, which is most likely to be related to father's migration for work. Father's presence misses significance when the IV approach is used. Mother's presence, on the other hand, increases the likelihood that a student joins the general stream and is significant even when using the IV approach but only at the 10% level. Students in rural Upper Egypt are less likely to go to the general stream, but the effect is not significant under the IV method.

As for preparatory school characteristics, the multiple-shift and the corporal punishment variables have a negative impact as one would expect, but their impact is statistically insignificant. However, the computer use variable has a significant positive impact on joining the general stream.

Turning to the tutoring equation (column 3), I find that the results are generally consistent with results obtained in Elbadawy et al. (2006). For example, the wealth variables are playing an important role with respect to taking tutoring. Father's absence, which is often caused by labor migration, has a positive effect on taking tutoring which is expected to be brought about by a positive migration income effect that is not fully captured by the wealth variables. Living in rural Upper Egypt has a negative effect on the probability of taking tutoring.

Unlike Elbadawy et al. (2006), this paper has the grade repetition and the preparatory school quality variables which were available from ELMPS 06. Grade repetition in the primary level does not significantly affect tutoring in the preparatory level. This seems to indicate that the tutoring effect on streaming will not be distorted by having weaker students more likely to receive remedial tutoring or less likely to get tutoring if their parents prefer to invest in academically promising siblings. The indicator on the use of corporal punishment in the school attended at the preparatory level has a significantly positive effect on the likelihood of participating in private tutoring classes. This may be related to a school environment where students are pressured by teachers to employ them as tutors.

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[26] The "condivreg" version I use was developed by Mikusheva and Poi (2006) as a newer version of an earlier "condivreg" command that was created by Moreira and Poi (2003). The newer version uses a simpler and improved computation method. Both deal with linear models with a single endogenous regressor.

[27] The coverage-corrected confidence set based on the Anderson-Rubin statistic is [-2.020408, 1.295237] while that based on the Lagrange Multiplier is [-2.020408, 1.295237].

[28] I also constructed 95% confidence intervals for the marginal effect of tutoring on joining the general secondary stream in the probit and IV-probit models. For the probit model, the confidence interval is [0.049464, 0.192915] while for the IV-probit, it is [-1.17754, 0.98953]. For the OLS model, the confidence interval is: [0.0348761, 0.1391957]. Note that in models controlling for endogeneity (i.e., IV-probit and 2SLS), the confidence intervals contain zero.

5. Conclusion

As seen above, without controlling for endogeneity, the tutoring effect is positive. The effect is mitigated when the instrumental variable estimation is used and becomes statistically indistinguishable from zero. While it is not unequivocal that tutoring is endogenous, I give more weight to the insignificant effect as it is better to control for endogeneity than not. One improvement to the instrument variable, which can help with its power, is to have it distinguish between teaching and administrative staff. If the staff is not evenly distributed, e.g., if administrative staff is proportionally more likely to be in large urban areas in a setting like Egypt where education is largely centralized, the instrument variable used in the analysis may be distorted. Having a variable that only includes teaching staff is possible if using the individual-level Census 96 data where the sector of work variables are more detailed. However, this data is confidential and doing such analysis is conditional on being able to acquire the data.

One limitation to the analysis is that it cannot identify the different tutoring effects. Tutoring participation may be cumulative, and participation in some grades may be more critical than others. Ideally, a tutoring measure would reflect the whole history of tutoring in different grades. This would have the benefit of distinguishing between students who never take tutoring, those who take it in particular grades and those who take it in all grades. However, what is available is an imperfect snapshot indicator of tutoring that only measures tutoring participation in the grade attended by a student at the time of the survey.

Another limitation is that the analysis only looks at the effect of taking tutoring and not the effect of tutoring quality or tutoring spending. Even though information is available on tutoring spending, I was unable to examine its effect on secondary streaming. This is because I do not expect that the variable used to instrument for the likelihood of taking tutoring would be a good instrument for spending on it. While it can capture the supply of tutors, it does not capture the tutoring fees charged by tutors or the tutoring quantity demanded by households. Also, tutoring fees, which affect the level of tutoring spending, can vary by quality and a proper instrument would require being able to adjust for quality, which is something not possible given the available data. I am deferring the examination of the effect of tutoring spending to the future.

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Table 1: Variable Means and Standard Deviations in the Sample*

Variables	Unweighted		Weighted	
	Mean	Standard Deviation	Mean	Standard Deviation
Dummy for ever-joining the general stream	0.44	0.50	0.44	0.50
Dummy for taking tutoring in 98	0.60	0.49	0.55	0.50
Percentage working in educ. sector at the local level	4.53	2.24	N/A	N/A
Female	0.48	0.50	0.46	0.50
Age in 98	13.59	1.35	13.66	1.35
Age in 98, squared	186.50	37.80	188.46	37.78
Eldest child	0.25	0.43	0.23	0.42
Repeated grades in primary level	0.03	0.16	0.03	0.16
F.* at least reads and writes	0.73	0.44	0.68	0.46
F. at least lower intermediate	0.55	0.50	0.50	0.50
F. at least intermediate	0.37	0.48	0.32	0.47
F. at least above intermediate	0.19	0.40	0.17	0.37
F. at least university and above	0.15	0.36	0.13	0.34
M.* at least reads and writes	0.49	0.50	0.42	0.49
M. at least lower intermediate	0.39	0.49	0.32	0.47
M. at least intermediate	0.25	0.43	0.20	0.40
M. at least above intermediate	0.11	0.31	0.09	0.28
M. at least university and above	0.07	0.26	0.06	0.23
HH* in second lowest quintile	0.19	0.39	0.20	0.40
HH in third quintile	0.21	0.41	0.21	0.41
HH in fourth quintile	0.19	0.39	0.19	0.39
HH in fifth quintile	0.23	0.42	0.24	0.43
F. present in HH in 98	0.89	0.32	0.89	0.31
M. present in HH in 98	0.98	0.14	0.98	0.14
Prep. school operated in shifts	0.38	0.48	0.40	0.49
Computer use	0.46	0.50	0.45	0.50
Use of corporal punishment	0.91	0.28	0.91	0.28
Prep. teacher-pupil ratio in the gov.	21.44	3.74	N/A	N/A
Alexandria and Suez Canal	0.13	0.34	0.09	0.28
Urban Lower Egypt	0.17	0.38	0.11	0.32
Urban Upper Egypt	0.19	0.40	0.08	0.28
Rural Lower Egypt	0.20	0.40	0.33	0.47
Rural Upper Egypt	0.15	0.36	0.25	0.43

Note: * Sample = was a preparatory student in 1998 and in 2006 has been to either of the secondary streams. Father (F.), Mother (M.), Household wealth index (HH).

Table 2: Effect of Private Tutoring on Secondary Streaming[1]

			1	2	3
				IV-Probit	
	Variable Name	Variable Description	Probit	Outcome Eq.	Tutoring Eq.
Child Characteristics	tut_98	Dummy for taking tutoring in 98	0.308***	-0.237	
			(0.0940)	(1.397)	
	peduc (IV variable)	% working in educ. at the local level			0.0183**
					(0.00805)
	Female	Female	0.173**	0.153	-0.0275
			(0.0869)	(0.106)	(0.0273)
	age_98	Age in 98	0.0946	0.196	0.209
			(0.468)	(0.523)	(0.147)
	age_98sq	Age in 98, squared	-0.00572	-0.00913	-0.00719
			(0.0167)	(0.0184)	(0.00525)
	Eldeschild	Eldest child in 98	0.0898	0.0972	0.0213
			(0.104)	(0.103)	(0.0322)
	repeat_prim	Repeated grades in primary level	-1.013***	-0.932**	0.0854
			(0.389)	(0.475)	(0.0848)
HH Characteristics	**Father Education**	**(omitted=illiterate or above)**			
	f_RW_atl98	F. at least reads and writes	0.209	0.244*	0.0755*
			(0.128)	(0.145)	(0.0422)
	f_linterm_atl98	F. at least lower intermediate	-0.257*	-0.244	0.0107
			(0.140)	(0.148)	(0.0463)
	f_interm_atl98	F. at least intermediate	0.400***	0.375**	-0.0211
			(0.146)	(0.172)	(0.0491)
	f_abvinterm_atl98	F. at least above intermediate	0.559**	0.572**	0.0541
			(0.248)	(0.244)	(0.0738)
	f_univabv_atl98	F. at least university and above	0.350	0.262	-0.150**
			(0.279)	(0.370)	(0.0761)
	Mother Education	**(omitted=illiterate or above)**			
	m_RW_atl98	M. at least reads and writes	0.0377	0.0547	0.0344
			(0.147)	(0.150)	(0.0487)
	m_linterm_atl98	M. at least lower intermediate	0.119	0.124	0.0153
			(0.169)	(0.167)	(0.0573)
	m_interm_atl98	M. at least intermediate	0.153	0.177	0.0369
			(0.163)	(0.168)	(0.0543)
	m_abvinterm_atl98	M. at least above intermediate	0.743**	0.636	-0.149*
			(0.301)	(0.441)	(0.0819)
	m_univabv_atl98	M. at least university and above	0.0612	0.0876	0.0494
			(0.430)	(0.424)	(0.0934)
	Wealth Quintiles	**(omitted=lowest quintile)**			
	qw98_2	HH in second quintile	0.0729	0.171	0.176***
			(0.149)	(0.282)	(0.0461)
	qw98_3	HH in third quintile	0.465***	0.553**	0.177***
			(0.148)	(0.235)	(0.0468)
	qw98_4	HH in fourth quintile	0.430***	0.550*	0.228***
			(0.159)	(0.309)	(0.0506)
	qw98_5	HH in fifth quintile	0.570***	0.717*	0.287***
			(0.173)	(0.368)	(0.0545)
	f_pres98	F. present in HH in 98	-0.251*	-0.322	-0.147***
			(0.140)	(0.211)	(0.0443)
	m_pres98	M. present in HH in 98	0.607*	0.598*	0.00727
			(0.343)	(0.345)	(0.103)
Preparatory School	shift_prep06	Prep. school operated in shifts	-0.138	-0.130	0.00634
			(0.0913)	(0.0949)	(0.0287)
	comp_prep	Computer use	0.270***	0.254**	-0.0152
			(0.0898)	(0.109)	(0.0283)
	punish_prep	Use of corporal punishment	-0.184	-0.116	0.108**
			(0.164)	(0.246)	(0.0499)
Community Characteristics	tchr_pupl_prep	Prep. teacher-pupil ratio in the gov.	0.0122	0.00867	-0.00219
	Regions	**(omitted=Greater Cairo)**	(0.0134)	(0.0164)	(0.00450)
	region2_98	Alexandria and Suez Canal	-0.0166	0.0487	0.116**
			(0.167)	(0.233)	(0.0521)
	region3_98	Urban Lower Egypt	-0.00272	0.111	0.145**
			(0.167)	(0.330)	(0.0583)
	region4_98	Urban Upper Egypt	-0.0974	-0.0212	0.0611
			(0.171)	(0.261)	(0.0609)
	region5_98	Rural Lower Egypt	-0.201	-0.136	0.0846*
			(0.160)	(0.238)	(0.0513)
	region6_98	Rural Upper Egypt	-0.324*	-0.422	-0.217***
			(0.180)	(0.284)	(0.0560)
	Constant	Constant	-1.854	-2.329	-1.186
			(3.288)	(3.402)	(1.039)
	Observations		1161	1161	1161

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. 1 Sample restriction: was a preparatory student in 1998 and in 2006 has progressed beyond the secondary branching point. Dependent variable = 1 if joined the general secondary stream.

Table 3: Effect of Private Tutoring on Secondary Streaming, Linear Models[1]

			1	2	3
				2 SLS	
	Variable Name	**Variable Description**	**OLS**	**Outcome Eqn.**	**Tutoring Eqn.**
Child Characteristics	tut_98	Dummy for taking tutoring in 98	0.0870***	-0.0187	
			(0.0266)	(0.396)	
	peduc (IV variable)	% working in educ. at the local level			0.0183**
					(0.0082)
	Female	Female	0.0500**	0.0472*	-0.0275
			(0.0248)	(0.0267)	(0.0276)
	age_98	Age in 98	0.00296	0.0238	0.2087
			(0.134)	(0.154)	(0.1493)
	age_98sq	Age in 98, squared	-0.000721	-0.00144	-0.0072
			(0.00476)	(0.00544)	(0.0053)
	Eldeschild	Eldest child in 98	0.0242	0.0261	0.0213
			(0.0292)	(0.0298)	(0.0327)
	repeat_prim	Repeated grades in primary level	-0.193**	-0.182**	0.0854
			(0.0768)	(0.0860)	(0.0860)
HH Characteristics	**Father Education**	**(omitted=illiterate or above)**			
	f_RW_atl98	F. at least reads and writes	0.0671*	0.0753	0.0755*
			(0.0384)	(0.0487)	(0.0428)
	f_linterm_atl98	F. at least lower intermediate	-0.0778*	-0.0767*	0.0107
			(0.0420)	(0.0419)	(0.0469)
	f_interm_atl98	F. at least intermediate	0.152***	0.150***	-0.0211
			(0.0446)	(0.0452)	(0.0498)
	f_abvinterm_atl98	F. at least above intermediate	0.165**	0.171**	0.0541
			(0.0670)	(0.0701)	(0.0748)
	f_univabv_atl98	F. at least university and above	0.0824	0.0668	-0.1499**
			(0.0692)	(0.0902)	(0.0772)
	Mother Education	**(omitted=illiterate or above)**			
	m_RW_atl98	M. at least reads and writes	0.00809	0.0117	0.0344
			(0.0442)	(0.0459)	(0.0494)
	m_linterm_atl98	M. at least lower intermediate	0.0502	0.0516	0.0153
			(0.0520)	(0.0519)	(0.0581)
	m_interm_atl98	M. at least intermediate	0.0538	0.0594	0.0369
			(0.0489)	(0.0529)	(0.0550)
	m_abvinterm_atl98	M. at least above intermediate	0.198***	0.182*	-0.1489*
			(0.0744)	(0.0954)	(0.0830)
	m_univabv_atl98	M. at least university and above	-0.110	-0.105	0.0494
			(0.0848)	(0.0863)	(0.0947)
	Wealth Quintiles	**(omitted=lowest quintile)**			
	qw98_2	HH in second quintile	0.00975	0.0292	0.1762***
			(0.0420)	(0.0839)	(0.0467)
	qw98_3	HH in third quintile	0.139***	0.158*	0.1771***
			(0.0426)	(0.0853)	(0.0475)
	qw98_4	HH in fourth quintile	0.132***	0.158	0.2284***
			(0.0458)	(0.107)	(0.0513)
	qw98_5	HH in fifth quintile	0.166***	0.198	0.2869***
			(0.0495)	(0.130)	(0.0552)
	f_pres98	F. present in HH in 98	-0.0654	-0.0811	-0.1469***
			(0.0404)	(0.0712)	(0.0449)
	m_pres98	M. present in HH in 98	0.168*	0.170*	0.0073
			(0.0932)	(0.0926)	(0.1041)
Preparatory	shift_prep06	Prep. school operated in shifts	-0.0380	-0.0374	0.0063
			(0.0260)	(0.0260)	(0.0291)
	comp_prep	Computer use	0.0815***	0.0798***	-0.0152
			(0.0256)	(0.0263)	(0.0287)
	punish_prep	Use of corporal punishment	-0.0454	-0.0335	0.1080**
			(0.0454)	(0.0633)	(0.0506)
Community Characteristics	tchr_pupl_prep	Prep. teacher-pupil ratio in the gov.	0.00357	0.00297	-0.0022
			(0.00385)	(0.00442)	(0.0046)
	Regions	**(omitted=Greater Cairo)**			
	region2_98	Alexandria and Suez Canal	0.000745	0.0134	0.1160**
			(0.0474)	(0.0667)	(0.0529)
	region3_98	Urban Lower Egypt	0.00445	0.0266	0.1451**
			(0.0467)	(0.0948)	(0.0591)
	region4_98	Urban Upper Egypt	-0.0152	-0.00130	0.0611
			(0.0477)	(0.0703)	(0.0617)
	region5_98	Rural Lower Egypt	-0.0575	-0.0462	0.0846
			(0.0458)	(0.0621)	(0.0520)
	region6_98	Rural Upper Egypt	-0.0860*	-0.108	-0.2170***
			(0.0509)	(0.0953)	(0.0568)
	Constant	Constant	0.0683	-0.0369	-1.1859
			(0.940)	(1.013)	(1.0533)
	Observations		1161	1161	1161

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. 1 Sample restriction: was a preparatory student in 1998 and in 2006 has progressed beyond the secondary branching point. Dependent variable = 1 if joined the general secondary stream.