The Impact of Free Secondary Education:

Experimental Evidence from Ghana[1]

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Abstract

Following the widespread adoption of free primary education, African policymakers are now considering making secondary school free. We exploit randomized assignment to secondary school scholarships among 2,064 youths in Ghana, combined with 11 years of follow-up data, to establish that scholarships increase educational attainment (at the secondary and the tertiary levels), knowledge, skills, and preventative health behaviors, while reducing fertility, especially for women. Ten years after receipt of the scholarship, winners show private labor market gains, primarily in the form of better access to jobs with rents. We develop a simple model to interpret the labor market results and think through the welfare impact of free secondary education, and the extent to which it depends on the presence of credit constraints, biased beliefs, imperfect altruism and the characteristics of public sector employment. We also show that non-experimental machine learning estimates of the returns to education do not systematically match IV estimates based on random scholarship assignment.

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1 Introduction

Following the widespread adoption of free primary education in low-income countries and the subsequent surges in primary school enrollment rates, policymakers' attention has shifted to secondary school. The U.N's new Sustainable Development Goals call for "... free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes". In Ghana, the setting of this study, debates about free secondary education were central in the last three presidential elections.

Since secondary education is much more expensive than primary education, and making secondary school free would generate a transfer to the generally wealthier households where parents are already sending their children to secondary school, it seems important to assess the extent to which free secondary education would induce more children to attend secondary school, and to determine whether the strong correlations between secondary education and lower fertility, better reproductive health, female empowerment, technology adoption, and greater civic knowledge and participation reflect causal effects. [2] Policymakers may also want to know the extent to which rapidly expanding access to secondary education will actually produce additional learning, given the weak preparation provided by many primary schools and the quality of existing secondary schools (e.g., Pritchett, 2001). Finally, a key question is whether it will generate either private or social labor market gains given that education levels in poor countries are already very high relative to both the historical benchmarks for much richer economies (Pritchett, 2018)[3] and the rationing of government jobs that command rents (Murphy et. al. 1991; North, 1990). Rapidly expanding education may be problematic if young people see secondary education as promising access to tertiary education and ultimately a government job,

[2] See UNGEI, 2010; Warner, Malhotra and McGonagle, 2012; Ackerman, 2015.

[3] For example, in Ghana average years of education among those 15 years old and above in 2010 was 7.8, equal to the level in the UK in 1970, even though the GDP per capita in Ghana in 2010 was less than a fifth that of the UK in 1970.

but the number of such jobs is limited. Such a situation may lead to a cohort of "over-educated" young people, frustrated in their aspirations (e.g. Krueger and Maleckova 2003; Heckman, 1991).

This paper provides experimental evidence on the impacts of free secondary school. Senior high school in Ghana has historically been limited based both on a gateway exam administered at the end of grade 8, which only roughly 40% of junior high school entrants pass, and by annual tuition fees, corresponding to about 20% of GDP per capita.[4] In this paper, we eased secondary school access for some youth by focusing on the financial barrier. In 2008, full scholarships were awarded to 682 adolescents, randomly selected among a study sample of 2,064 rural youth who had gained admission to a public high school but did not immediately enroll. Follow-up data were collected regularly until 2019, when these youth were on average 28, with a minimal attrition rate of 6%.

We find that scholarships increased educational attainment. Winners were 25 percentage points (51%) more likely to enroll in secondary school and spent 1.23 more years in secondary education than non-winners. However, back of the envelope calculations suggest that for every marginal student induced to attend secondary education by subsidies, 15 would receive transfers (assuming that the prospect of free secondary education does not lead more marginal people to successfully finish primary education.)

The increase in education translated into an increase in cognitive skills. Five years into the study, scholarship winners scored on average 0.16 standard deviations higher on a series of practical math and reading comprehension questions modelled on the PISA. Winners were more knowledgeable about national politics and more likely to know and use modern technologies.

[4] A complete senior high school education, currently three years, would cost about 70% of GDP per capita, when additional clothing, exam and material fees are included. Around 70% of junior high school entrants go on to take the BECE (see http://www.moe.gov.gh/assets/media/docs/FinalEducationSectorReport-2013.pdf) and 60% of BECE takers pass (see for example http://www.ghanaweb.com/GhanaHomePage/economy/artikel.php?ID=149100 or http://citifmonline.com/2014/06/16/only-60-of-bece-candidates-make-it-to-shs-ges/).

By 2013, when most participants were around age 22, women who had received a scholarship were 6.6 percentage points less likely to have ever been pregnant – a 14% drop compared to the rate in the comparison group (48.3%). The gap persists in the following years, suggesting it is not just driven by students postponing fertility until they are out of school. By 2017, at age 26 on average, women in the treatment group were still 7.0 percentage points (10%) less likely to have ever been pregnant and had 0.185 fewer children. Both men and women engaged in more preventative health behaviors and men reported engaging in less risky sexual behavior.

Access to free secondary education increased the chance of having ever enrolled in tertiary education by 4 percentage points on a base of 15.2 percent (+26%) and increased the probability of completing tertiary as of 2019 by 3.5 percentage points on a base of 8.7% (+40%). These effects are concentrated among women.

Scholarship winners obtained better jobs along various dimensions, but it is unclear whether these private benefits reflect social benefits or just access to rationed formal sector jobs. Nine years after scholarship receipt and 3-4 years after on-schedule secondary graduation, the scholarship increased the odds of being a public-sector employee by 3.3 percentage points, more than double the baseline rate (from 2.8 to 6.1%). Wage premia and other perks for public sector jobs are high, particularly for those with tertiary education, both in our data and in other work (Aryeetey and Baah-Boateng, 2016).[5] As of 2019, treatment group members were more likely to have formal employment contracts and jobs with benefits. The scholarship did not increase hourly earnings and in some specifications decreased them.

[5] Barton, Bold and Sandefur (2017) found a wage premium of over 100% for public school teachers in Kenya.

We interpret these labor market results using a simple model which nests the possibility that education increases human capital, productivity, and thus hourly wages and the possibility that education is used to ration jobs with rents. The model allows the labor market to include competitive self-employment and private employment sectors along with a premium sector in which jobs with high fixed wages are rationed by education. Our results are not consistent with a strong labor market effect driven entirely by the first channel, since we do not see an increase in hourly wages or a significant increase in private sector jobs. We cannot exclude the hypothesis that secondary education affects labor market outcomes only by helping people compete for jobs that yield rents. However, we also show that, given the variation we have, one cannot rule out that both channels are at play, since the model implies that the highest ability workers in the treatment group may sort into tertiary education and premium sector employment, making it difficult to assess the treatment effect of education on private sector wages for any individual.

Even allowing for the difficult macroeconomic conditions that Ghana has been experiencing since our study sample graduated, it is clear there is a substantial gap between actual labor market impacts and the stated expectations of students and their parents. At baseline students overwhelmingly expected to go into positions that require tertiary education and that are associated with high rates of public sector jobs. 70% thought they would be a government employee or in a profession dominated by government employees by the age of 25 if they completed senior high school. In reality, only 6% of those who completed senior high school held these positions by the age of 26, and 12% by age 28. This misperception could potentially lead to distortions in the amount and type of education individuals chose to pursue.

In the model, households invest in education given their perceptions of returns to education and their child's potential for success in school, but may be subject to credit constraints and may not completely internalize children's future wages. We allow for households' preferences regarding their children to differ by gender. Marginal boys induced to attend school perform poorly relative to inframarginal boys, but marginal girls perform about as well as inframarginal girls. This finding is consistent with the view that most households are already sending those boys with the best chance of making it to tertiary education to secondary school, but that there is heterogeneity in preferences toward girls' education, with some households sending talented girls to secondary school only if they obtain scholarships.

Our results contribute to a large literature on the impact of education in the developing world. There are surprisingly few well-identified studies on the impact of secondary schools in this context. Some argue that conditional cash transfers that increase educational attainment do not increase learning (Reimer et. al, 2016), but it is not clear these studies are adequately powered. We are aware of no randomized controlled trial (RCT) – on the labor market impact of post-elementary education and only two studies based on regression discontinuities – exploiting admission cutoffs in test scores in Kenya (Ozier 2016) and scholarship eligibility cutoffs based on a dropout-risk score in Cambodia (Filmer and Schady 2014). One study exploits the graduate rollout of a large-scale fee elimination for secondary school girls in The Gambia, but outcomes are limited to educational outcomes. Our approach can be seen as identifying the impact of relaxing financial constraints to obtaining education, while the regression discontinuity approach can be seen as the impact of relaxing academic qualifications for secondary school, and of course the relevant treatment effects may differ (Lang, 1993; Card, 1999). Our results also point to an important methodological lesson that premature findings may be misleading or will not provide a complete picture. Many outcomes were not consistent year to year, and suggest that people take time to find their reach in the labor market.

Since randomized controlled trials of secondary education are rare, but surveys with data on both education and earnings abound, it would be useful to gauge how much can be learned from observational data. Our setup provides us with the rare opportunity to perform a modern version of the Lalonde (1986) exercise, putting the new generation of nonparametric statistical methods ("machine learning") to the test. Specifically, we ask: can our experimental estimates be recovered from observational data (the comparison group) by controlling flexibly for the very rich set of control variables that we have? We apply the Double Machine Learning (DML) method proposed in Chernozhukov et al. (2018) to control flexibly for the very rich set of control variables collected at baseline (recall that we administered surveys to both the guardian and the student herself at baseline, so we have around 2,000 controls). We first show that non-experimental estimates of the effect of education calculated using OLS estimates exceed IV estimates based on experimental variation of education's effect on learning gains, reductions in fertility and reductions in risky sexual behavior but are lower than experimental IV estimates of impacts on labor market outcomes and preventative health behavior. We find that the DML only partially closes the gap between the OLS and the IV, and not for all outcomes, even when reweighing the observations so that the ML sample looks like the compliers observationally.

The paper proceeds as follows. Section 2 describes the context. Section 3 presents a model through which we interpret our results. Section 4 describes the data. Section 5 presents the impacts on educational attainment and some estimates of the fiscal costs. Section 6 discuss the reduced form impacts on knowledge, skills and attitudes, fertility and marriage. Section 7 discuss the labor market outcomes. Section 8 compares the OLS estimates with Instrumental Variable and Double Machine Learning-debiased estimates. Finally, section 9 concludes.

2 Context

This section provides background on Ghana's education system and labor market context.

2.1 Ghana's Education System

Formal education in Ghana begins with two years of kindergarten, six years of primary school, and three years of junior high school. Primary and junior high school are free and enrollment rates are close to 95% in primary school and are around 75% in junior high. At the end of junior high school, students take the Basic Education Certification Examination (BECE) and those with high enough grades qualify for senior high school. Passing rates are low. Around 70% of junior high school entrants go on to take the BECE and 60% of BECE takers pass. Ajayi (2014) estimates that at least 20% of those admitted do not enroll in senior high school the following year, and many cite costs as the reason. In 2011, government-approved tuition fees for day (non-boarding) students in senior high school were around 500 Ghana cedis per year, a very large sum in a country where the per capita GDP that year was 2400 Ghana cedis.[6] Many students do not have a day school within easy access since there are only around 700 senior high schools for the entire country compared to over 9,000 junior high schools. These students must therefore attend a boarding school, which tends to be more expensive. As of 2010, girls were 6 percentage points (20%) less likely to ever reach senior high school. Some of those who do not enroll in senior high school enroll in Technical and Vocational Institutes (TVIs).[7]

[6] See http://www.statsghana.gov.gh/docfiles/GDP/EconomicPerformance_2011.pdf

[7] TVI students do not have to take any core academic classes and cannot go on to tertiary. TVIs are a relatively minor part of Ghana's education system, with less than 10% the enrollment of senior high school. In 2008, there were 43,592 full-time TVI students compared to the 486,085 senior high school students (MoE Ghana, 2008).

Students who complete senior high school and do well on the senior high school finishing exam (the West African Senior School Certificate Examination or WASSCE) may be admitted to tertiary programs, including degree programs at universities, less prestigious diploma programs, and government training programs, for example for teachers and nurses. There is a one-year gap between completion of senior high school and admission into university or training colleges. Students who do not score well enough on the exam to secure tertiary admission can retake the senior high school finishing exam any number of times. Tertiary education is expensive. Two types of tertiary programs, nursing and teaching, are heavily subsidized through government stipends, though this policy was put on hold in 2013– precluding youth in our study sample to benefit from it. The policy was reinstated (though with stipends cut in half) in 2017.

2.2 The Ghanaian Labor Market

As in many developing countries, Ghana has very high premia for public sector positions, particularly those requiring tertiary education. Finan, Olken and Pande (2015) find a wage premium of at least 59% in Ghana, using the 2013 STEP Skills Measurement Survey. Note that public sector jobs provide substantial benefits beyond wage benefits both because they provide a great deal of job security and because they typically carry some substantial benefits. Access to these jobs is historically limited to those with certain types of tertiary education.

3 Model

This section provides a simple model with which to interpret differences in outcomes between the treatment and comparison group, interpret treatment-effect heterogeneity by gender, and understand implications of the data for the potential welfare impact of education subsidies. In particular, the model can be used to bound the production function impact of increased education when secondary education subsidies may not only affect earnings within sectors, but also move people from the labor market to tertiary education, and within the labor market may move people from self-employment to employment in a competitive private employment sector or from employment in a competitive private sector to public sector jobs that pay rents, thus generating endogenous compositional shifts that could otherwise lead to underestimation of treatment effects on earnings and welfare.

We assume that parents make educational decisions for children in part based on information on child ability that is unobserved to the econometrician. Since education and child ability are taken to be complements, parents will educate children above a threshold level of ability. This implies that non-experimental estimates of the return to education may be subject to omitted variable bias, and that the estimated treatment effect using random scholarship assessment will capture the average treatment effect on marginal children who are induced to obtain education by the subsidy.

Educational decisions made by parents may be distorted away from the level that maximizes total output by their credit constraints, misperceptions of child ability and imperfect altruism, which can appear in the form of gender biases. Subsidies for education will lead parents to reduce the threshold level of ability above which they educate children. If parents are homogeneous in wealth and are perfectly altruistic regarding their children's welfare, then learning and labor market outcomes among the marginal children induced to attend school by free secondary education will be worse than those among inframarginal children who would have been educated anyway. If, on the other hand, variation in secondary education is not determined primarily by variation in students' ability, but rather by variation among parents in credit constraints or preferences regarding children's welfare, then even though education subsidies lead each individual household to reduce the threshold ability level for making educational investments, at the level of the society as a whole, learning and labor market outcomes may be as strong or stronger among marginal children induced to attend secondary school by free education as among inframarginal children who would have attended school in the comparison group.

The model suggests that education subsidies will be more likely to increase overall welfare if labor market outcomes for the marginal student induced to attend schools by subsidies are favorable relative to those of inframarginal students, and if productivity in the premium sector is sufficiently higher than that in the private sector.

Subsection 3.1 lays out assumptions on the human capital production process and on the labor market. Subsection 3.2 solves the model backwards, starting with the final period static equilibrium in which workers choose their labor market sector and effort level taking education and skill as given, and characterizes the household's decisions regarding educational investment. Subsection 3.3 addresses welfare.

3.1 Assumptions

Timing: At t=0, parents choose whether or not to enroll their child in secondary education. At t=1, children are either in secondary education or the labor market. Children who attend secondary education and do well enough academically go on to tertiary education at t=2, while others enter the labor market. By t=3, all children are in the labor market. For simplicity, we will assume that children's consumption takes place towards the end of their lives in t=3 and that households cannot save or borrow.

Utility function: Households each have one child and allocate wealth drawn from a distribution $H(.)$ with lower support $\underline{y} \in (0,1+\ c_C)$ between consumption and educational investment to maximize a quasilinear utility function. In general, we will take this to be $u_i =\ lnx_{io}^1\ +\ x_{io}^2\ + \lambda_{ig}u_{ci} - \frac{1}{2}e_i^2$, where x_{i0}^1 denotes household i's consumption of good 1 at $t = 0$, whose marginal utility is diminishing, x_{i0}^2 denotes the consumption of good 2 for which utility is linear in consumption, u_{ci} denotes the child's welfare in the future, and e_i denotes effort. The parameter λ_{ig} ≤ 1 represents the weight parents put on their child's welfare.[8] We allow this to differ based on their child's gender; the subscript g indexes gender and $g\ =\ f$ denotes a female and $g\ =\ m$ denotes a male. We assume $\lambda_{if}\ \leq\ \lambda_{im}$. Parents are assumed to have already worked, and hence do not face a choice of effort, but children will trade off effort and consumption when they reach the labor market. Therefor $e_i = 0$ for parents and the utility function of children take the form of $lnx_i^1\ + x_i^2 - \frac{1}{2}e_i^2$. Moreover, we assume the price of good 1 and that of good 2 are taken as given, both being 1.

Human Capital Production Function: Worker skill depends on the highest level of education completed h_i, initial ability a_i, and a random noise term ε_i: $s_i\ =\ f(h_i, a_i)\ + \varepsilon_i$. We assume that $\frac{\partial f}{\partial h}, \frac{\partial f}{\partial a} > 0$ and that initial ability and education are complements in the human capital production function $\frac{\partial^2 f}{\partial h \partial a} > 0$. The highest level of education can be primary $(h_i = 1)$, secondary $(h_i = 2)$ or tertiary ($h_i = 3$). Initial ability is randomly drawn from some continuous distribution $G(.)$ with support $[\underline{a}, \overline{a}]$. We assume that initial ability is independent of household wealth and of gender. ε, the error term, in human capital production is mean zero, independently and identically drawn from

[8] One possible way to endogenize this is that parents' ability to recoup investments in children's education may differ with gender.

a continuous distribution $E(.)$ with lower support of $\underline{\varepsilon} > \frac{(1+c_C)}{A_h} - \underline{\eta} - f(1, \underline{a})$. (Notations in this expression are defined below).

Denote the cost of secondary education in time and out-of-pocket outlays as c. As the scholarship will lower the cost of education, the treatment group $(\boldsymbol{T}_i = 1)$ will face a lower cost of education c_T than the control group $(\boldsymbol{T}_i = 0)$ that faces c_C. Therefore, $c_i = \ c_C \ if \ (\boldsymbol{T}_i = 0)$ and $c_T \ if \ (\boldsymbol{T}_i = 1)$. For simplicity, rather than model the choice of tertiary education, we assume that all children who complete secondary education and do well enough academically automatically go on to tertiary education.[9]

Production function: Once skill is realized, workers enter a labor market with three sectors: a competitive self-employment sector, a competitive private sector labor market, and a premium sector in which jobs pay a premium above the market wage, and positions are rationed by tertiary education. Suppose self-employment production[10] is $Y_h = A_h s + e + \eta$, where s denotes workers' skill, e denotes effort and η is an idiosyncratic mean-zero time-varying shock with lower support $\underline{\eta}$. Production in the competitive private sector is $Y_p = A_p s + e - f_p + \eta$ where f_p represents a fixed cost of working in the private sector and $A_p > A_h$. Premium sector production is given by $Y_g = A_g s + e - f_g$ where f_g represents a fixed cost of working in the premium sector. The self-employment and private sectors are assumed to be perfectly competitive and we derive the

[9] For now, we abstract from the choice of tertiary education and assume that anyone who does well enough on the WASSCE exam to obtain admission to tertiary education finds it optimal to enroll. A simple way to endogenize this would be to assume the tertiary education premium is (or is perceived to be) very large.
[10] We conjecture that the results will generalize to a more general specification of the production functions where output is increasing in both arguments (dY/ds > 0 and dY/de >0) and the return to effort is decreasing ($d^2Y/de^2 \leq 0$).

wage in these sectors below. We assume that $f(3, \underline{a}) + \underline{\varepsilon} > \frac{f_p}{A_p - A_h}$, which ensures that all tertiary graduates prefer working in the competitive private sector than in the self-employment sector.

The wage in the premium sector is institutionally fixed at $w_g = A_p s + \phi - f_p$ where $\phi \geq 1/2$. Premium sector workers thus face no effort incentives and bear no risk. $\phi \geq 1/2$ ensures that they obtain greater utility than they would in the competitive private sector in expectation.

There are a fixed number of slots in the premium sector. We assume that these are restricted to those with tertiary education and that among those with tertiary education, the probability of obtaining a premium sector job is weakly increasing in skill. Public sector jobs requiring tertiary education, such as teachers and nurses, are the clearest example of premium sector jobs since many households saw education as a path to such jobs. However, the underlying concept is broader, and may also encompass certain private sector jobs, for example jobs in parastatals, or unionized jobs.

The probability of obtaining a premium job conditional on completing secondary education can be written as an increasing function of initial ability $p_{ig}(a_i)$. Parents believe that if their child enrolls in secondary schooling, he or she will complete it with probability $p_{is}(\hat{a}_i)$ which is increasing in the estimate of their child's initial ability $\hat{a}_i$.[11] Households have information on their child's junior high school performance, which we will interpret as a noisy signal of ability, as well as potentially private information on child ability. Thus, perceived and actual ability are positively correlated and the perceived probability of obtaining a premium sector job conditional on starting secondary school is therefore $p_{is}(\hat{a}_i) * p_{ig}(\hat{a}_i)$.

[11] For simplicity we assume here that parents know that how this likelihood depends on ability. However, this assumption can be relaxed to allow for a misperception in the functional form of $\hat{p}_{is}$ in addition to child's ability.

3.2 Characterizing the labor market equilibrium and education choices

As noted above, we solve the model backward. We first derive wages in each sector as a function of skill and effort, and then solve for workers' effort choices conditional on sector. Next, we solve for the labor market choices of children after realizing their education and skills, and finally solve for parental choices for child education as a function of parental wealth, child gender and perceived ability, and education subsidies.

Note first, however, that self-employed workers will receive actual production and will bear the risk associated with time-varying shocks to production. We will assume that firms in the competitive private sector can perfectly monitor and contract on effort, so employees do not bear the risk from the wage contract, but their employer bears the risk associated with time-varying shocks to production. Because the sector is competitive workers will have to bear the fixed per period cost of production in this sector in their wages.

The following proposition shows that given the assumptions above, all workers who are offered a premium sector job will take it and exert zero effort. Workers who don't obtain premium sector jobs will exert unit effort and choose to work in self-employment if their skill is less than $\frac{f_p}{A_p - A_h}$, and in the competitive private sector otherwise.

Proposition 1: (a) Premium sector workers will choose $e^* = 0$ while self-employed workers and competitive private sector workers will choose $e^* = 1.$ (b) Highly skilled workers with skill s> $\frac{f_p}{A_p - A_h}$ will prefer to work in the competitive private sector rather than the self-employment sector while those with skill s< $\frac{f_p}{A_p - A_h}$ will choose self-employment. (c) Highly skilled workers with s> $\frac{f_p}{A_p - A_h}$ and tertiary education will prefer to work in the premium sector.

The proof for Proposition 1, as well as all other proofs, are shown in Appendix A.

It is straightforward to calculate the private return to education given p_{is}, the probability of graduating secondary school given secondary enrollment, and p_{ig}, the probability of obtaining a premium job given secondary education (this is equal to the probability of obtaining tertiary education given secondary education times the probability of obtaining a premium job given tertiary education). Recall that these are increasing functions of initial ability, but we suppress that notation here. Given the labor market equilibrium, the perceived expected NPV of the child's welfare if enrolled in secondary school $(D_i = 1)$ is:

$$NPV|_{D_i=1} = p_{is}[p_{ig}u^*_{ig} + (1-p_{ig})\,(E[w_i|D_i = 1] - \frac{3}{2})] + (1-p_{is})NPV|_{D_i=0}$$

$$= p_{is}\left[p_{ig}\left(A_p s_i + \phi - f_p - 1\right) + \left(1-p_{ig}\right)\left(E[w_i|D_i = 1] - \tfrac{3}{2}\right)\right]$$

$$+(1-p_{is})NPV|_{D_i=0}$$

while the perceived expected NPV if the child is not enrolled in secondary education is $NPV|_{D_i=0} = E[w_i|D_i = 0] - \frac{3}{2}$. Let $\widehat{\Delta}_i(s_i) = NPV|_{D_i=1} - NPV|_{D_i=0}$ denote the gain in perceived expected NPV of the child's welfare if the household chooses to enroll the child in secondary school. Hence,

$$\widehat{\Delta}_i(s_i) = p_{is}\,[p_{ig}\,(A_p s_i + \phi + \tfrac{1}{2} - f_p - E[w_i|D_i = 0])$$

$$+(1-p_{ig})(E[w_i|D_i = 1] - E[w_i|D_i = 0])]$$ [12]

[12] As effort choice will be the same in the self-employment and competitive private sector, as derived in the proof for Proposition 1, it does not affect the NPV of welfare.

This perceived expected gain reflects partly the rent seeking possibility due to a premium sector job and partly the rewards for human capital which increases skill and therefore marginal product in the home and competitive private sectors. Denote the true private gain as $\Delta_i(s_i)$.

The utility maximization problem that the household faces is:[13]

$$\max_{\{D_i, x_{i0}^1, x_{i0}^2\}} \ln x_{i0}^1 + x_{i0}^2 + \lambda_{ig}\left(E[w_i|D_i = 0] - \frac{3}{2} + \widehat{\Delta_i} D_i\right)$$

$$\text{s.t. } x_{io}^1 + x_{io}^2 \le y_i - c_i D_i$$

The model implies that households are more likely to invest in secondary education the higher their estimate of their child's ability and that girls face a weakly higher threshold of ability than boys.

Proposition 2: (a) Each household will have a threshold level of child ability $a^*(g_i, c_i, y_i)$ and will choose $D_i = 1$ if $\hat{a}_i \ge a^*(g_i, c_i, y_i)$ and $D_i = 0$ otherwise. (b) This threshold level of ability will be greater for households in the comparison group compared to the treatment group. (c) Girls face a higher threshold level of estimated ability than boys.

Below we show that the impact of the scholarship on the average perceived ability of children enrolled in secondary education is ambiguous although for any individual household, receiving the treatment lowers perceived ability threshold for obtaining secondary schooling.

Proposition 3: (a) If all households have the same wealth and do not have a gender bias, then marginal children getting education in response to a subsidy will have lower perceived ability than inframarginal children. (b) If there is heterogeneity in wealth and some households are sufficiently poor, then within gender, marginal children can have higher perceived ability than the inframarginal

[13] As explained in the proof for Proposition 1, children will earn at least $w_i > 1 + c_C$ and hence will be consuming on the linear portion of their utility function. Their welfare therefore enters linearly in the parents' utility function. This condition seems reasonable since all the children in the sample completed primary education and scored well enough to pass the BECE exam and gain admission to secondary school, and since Ghana has recovered robust economic growth since 2017.

children. (c) If there is heterogeneity in parental altruism for their child's welfare, for example, because of gender bias, then marginal children can have higher perceived ability than inframarginal children.

Corollary: If parents' perception of child ability is accurate ($\hat{a}_i = a_i$), then with heterogeneity in wealth, marginal children can have higher ability than the inframarginal children, so will be more likely to complete secondary, go on to tertiary education, and get private competitive or premium sector jobs than the inframarginal children who were already obtaining education.

For expositional purposes, it is useful to consider the effects of the subsidy in the absence of the premium sector. This will lead to an increase in employment in the competitive private sector, a decrease in self-employment, and an increase in total earnings. But its effect on average earnings among the wage employed is ambiguous.

Proposition 4. In the absence of a premium sector, an education subsidy can increase or decrease the average earnings conditional on wage employment in the competitive private sector.

Paying for secondary education moves people from self-employment with low productivity to self-employment with higher productivity, competitive private sector and tertiary education. The following proposition shows how the treatment effect on labor market earnings in the short-term may constitute a lower bound.

Proposition 5. (a) The treatment effect on earnings in t=2 will be less than that in t=3. (b) The treatment effect on earnings in t=3 will underestimate the treatment effect on welfare. Combining (a) and (b), the treatment effect on earnings in t=2 will constitute a lower bound for the treatment effect on welfare in t=3.

3.4 Welfare Effects of Free Secondary Education

There are two types of social planners to be considered in the following propositions. One is unconstrained and has full information on children's ability and the other is constrained and knows less about children's ability than their parents. They are both assumed to weigh everyone equally, not to consider parental altruism, and to have access to lump sum transfers. Throughout this part, we assume economy is wealthy enough so that average initial wealth per household is greater than $1 + C_c$, which ensures that a household on average can consume positive amount of good 2 even if they send their children to secondary education. As we will show, under the assumptions above, the unconstrained social planner simply dictates everything, but the constrained social planner sometimes resorts to a decentralized price system and uses lump sum transfers to achieve efficiency.

Proposition 6: An unconstrained social planner will decide how much each household consumes and will dictate who goes to secondary education.

However, for a constrained social planner, who has less information about children's true ability, it's more reasonable to decentralize decision making with a price system for education and rectify distortions through taxes, subsidies and lump sum transfers. In the decentralized equilibrium, there are four possible sources of distortion. First, parents having decision rights but being only imperfect altruistic. Second, credit constraints. Third, difference between wage and productivity in the premium sector. Forth, biased estimation of children's ability. The following propositions address them respectively.

The following proposition isolates imperfect altruism and shows how, in the presence of partial altruism, the constrained social planner can achieve a more efficient equilibrium through lump sum transfers.

Proposition 7: If parents have full information on children's ability (i.e. $\hat{a} = a$), in the absence of the premium sector and credit constraints, the constrained social planner will tax the income of parents with $\lambda < 1$, and subsidize education.[14]

[14] This assumes that Budget Balance holds.

The following proposition isolates credit constraints and shows how a constrained social planner achieves a more efficient equilibrium through lump-sum transfer.

Proposition 8: If parents have full information on children's ability (i.e. $\hat{a} = a$), in the absence of the premium sector and imperfect altruism, the social planner will make a lump sum transfer from the rich households to the poor households.

The following proposition studies the distortion from the difference between wages and productivity in the premium sector and shows that the policy on education will go in different directions depending on the level of premium sector productivity.

Proposition 9: If premium sector exists, $\lambda = 1$, and $\hat{a} = a$, in the absence of credit constraints, the social planner will subsidize education if A_g is sufficiently greater than A_p, and tax education otherwise.

Parents are often subject to inaccurate estimation of their children's true ability. The following proposition studies the case where parents' perceived ability of their children is systematically biased. As we will show, the best reactions of the constrained social planner to parents' bias depends on the direction of this bias.

Proposition 10: In the absence of imperfect altruism, credit constraints, and the premium sector, if parents systematically overestimate their children's real ability by a constant *d*, the constrained social planner will tax education for all households and subsidize the income of households who send their children to secondary education by the same amount. If parents systematically underestimate children's real ability by a constant d, our result will go in the opposite direction.

The model has a number of implications for measurement. First, it suggests that Mincer regressions that do not control for child ability may overestimate the return to education for those induced to attend school by free education and thus highlights the importance of experimental measurement of the effects for this group, as we provide in this paper.

Second, it shows that measuring the labor market impact of education at t=2 while some participants are still in tertiary education will provide a lower bound on the causal impact of education on wages due to selection issues, but that it is possible to construct an upper bound on the labor market impact on education at t=2. We can do so by dropping those with the highest outcomes in the comparison group as Proposition 5 suggests. Developing causal estimates, rather than just bounds, may require waiting until people have had a chance to complete tertiary education and enter the labor market.

Third, it suggests that a comparison of the impact of free education on market wages will yield a lower bound on the impact on total wage earnings because an increase in education will move some people from self-employment to wage employment. Assuming that these workers are at bottom of the earnings distribution, we can construct an upper bound by looking, at=3, at the difference between wages conditional on employment in the comparison group and wages conditional on employment for the top 100-X percent of the distribution in the treatment group, where X is the percentage point difference in wage employment rates between treatment and control groups.

Fourth, it suggests that the effect of the education subsidy on wages will be lower bound on the effect on welfare for participants because those who obtain premium sector jobs will also benefit from these jobs in ways not captured by the increase in wages, in particular, by having to exert lower effort. Similarly, to the extent that some people may choose premium sector jobs with lower wages over private sector competitive labor market jobs with higher wages, the observed impact of increased education on wages conditional on private competitive labor market employment will be lower than the true production function effect of human capital on output in the competitive private sector labor market.

Finally, the model implies that to the extent that premium sector jobs are rationed by education or that households overestimate returns to education the private welfare effects of education subsidies will exceed their social welfare effects.

4 Data and Sample Characteristics

This section describes how we gathered data and the characteristics of our sample. Section 4.1 describes the sampling frame. Section 4.2 explains the scholarship program. Section 4.3 details the surveys used. Section 4.4 presents information on the baseline characteristics of the sample.

4.1 Sampling Frame

The sample frame for the study was constructed as follows. First, 5 out of the 10 regions in Ghana were included in the study.[15] Across these 5 regions, 54 out of the 170 districts in Ghana were selected because they had a high ratio of day students to boarding (typically richer) students (according to statistics from earlier years), and did not include the regional capital. We focused on day students for budget reasons and because as senior high school becomes more common we expect more students to be attending day schools. Across these 54 districts, we selected a total of 177 publicly funded senior high schools that accept day students. These senior high schools represented about 60% of all senior high schools in the selected districts as of 2008 (and about 25% of all SHS in the country). They are all co-ed, and typically have over 1,500 students, with an average pupil-teacher ratio of 22. Within each selected senior high school, all students officially admitted into the senior high school as of October 2008 were considered for eligibility.

[15] The three Northern regions and the Volta region were not selected because the Government of Ghana already ran a scholarship program in those regions at the time. Greater Accra was excluded given our focus on poorer areas.

To be considered eligible for the study, students needed to satisfy the following criteria: (1) To have been placed into one of the 177 study senior high schools by the Computerized School Selection and Placement System (CSSPS)[16]; (2) To have attended a junior high school in the same district (referred to as "in-district students") as the senior high school they were admitted to; (3) To have not yet enrolled in any senior high school by October 2008 (the school year had started in September).

Through visits to both senior and junior high schools, and various interviews with headmasters, teachers and other students conducted in October 2008, we identified 2,246 students eligible for the study. We also asked students why they did not enroll. 95% cited financial difficulties as the main reason, 2% cited pregnancies and 3% cited a variety of other reasons such as being injured, having a job or not liking the school they were placed in. Because students, headmasters and surveyors were unaware of the availability of scholarship at the time of initial surveying, we avoid problems of self-selection into the study sample. Each year fewer girls are admitted into senior high school than boys, so, in order to ensure we had enough eligible girls in the sample, we had to include girls who had graduated from junior high school in July 2007 and had gained admission into one of the 177 sampled senior high schools one year prior to the rest of the sample, but had still not enrolled as of October 2008.

In early January 2009, the 2,246 eligible students were called back to assess whether the student had enrolled or intended to enroll in a senior high school for the second term of the 2008-2009 school year. A total of 182 students who either had enrolled or intended to enroll in senior high school in the immediate term were dropped from the sample prior to randomization. The final study sample is thus

[16] The CSSPS is a centralized, merit-based admission system, which is based on the deferred-acceptance algorithm of Gayle and Shapley (1962) (Ajayi, 2013).

composed of 2,064 individuals (1,028 males and 1,036 females). Among the females, 746 had taken the junior high school finishing exam in 2008 and 290 had taken it in 2007.

4.2 Scholarship Program

The scholarship program was implemented by Innovations for Poverty Action (IPA) in Ghana, in partnership with the Ghana Education Services (GES), the implementing arm of Ghana's Ministry of Education, and Senior High School staff.

The scholarship covered the full tuition and fees for a day student for four years. The scholarship was paid directly to the school and covered the entire school bill. A typical senior high school bill for a day student is comprised of three items: government approved fees which are applied for all schools, PTA (Parents-Teachers Association) dues, and other levies and supplies, including exam fees. The latter two costs are school-specific. In addition to paying school fees, the scholarship also included payment for the final secondary school exam fee (WASSCE). Students who received the scholarship were only responsible for the cost of school materials, the cost of transportation to the senior high school and feeding costs (plus boarding costs if they chose to board). The total amount paid by the scholarship program varied slightly across courses and schools but averaged approximately 1,921 Ghana cedis (in 2016 GHX terms) per student who completed senior high school.

Winners were notified by phone in January 2009 and encouraged to immediately report to their placement senior high school (the senior high school where they had been placed into based on their performance on the junior high school finishing exam). Senior high school Headmasters were informed of the names of scholarship winners by phone and they also received an official letter from the Director-General of the Ghana Education Service and IPA with details on the scholarship scheme. All schools agreed to participate. Each senior high school received only few scholarship students (the median is 3 and the mean is 4, compared to cohort sizes of over 400 students on average).

This did not make our scholarship winners particularly special, as it is very common for schools to have students enroll as late as Term 2; in particular, students on the waitlist are notified late in Term 1 if those initially admitted have not reported and can be replaced.

4.3 Data

We use three main data sources: a baseline survey, an extensive follow-up survey administered in person after 5 years, and "callback" surveys (shorter phone surveys) administered in 2015, 2016, 2017 and 2019.

4.3.1 Baseline Survey

In November and December of 2008, prior to selecting the students for the scholarship, a baseline survey was administered to the youth themselves as well as to one of their guardians, most commonly the mother. The surveys included questions on perceptions of education, guardian literacy, values and beliefs, as well as modules on members of the household, household living conditions, and assets. After the survey, each student received a mobile phone.

4.3.2 Randomization

The final study sample of 2,064 youths was stratified by district, senior high school, junior high school, gender and BECE year. A third of students within each strata (682 in total) were assigned to the "treatment group" (a scholarship) while 1,382 students were assigned to the "comparison group" (no scholarship).

4.3.3 Sample Maintenance and Attrition

To enable high follow-up rates, mobile phones were distributed at the onset of the study to every youth, and study participants were sent mobile phone credit worth about USD1 twice a year, as an incentive for them to keep the phone number we have on file active. Once a year, we attempted to reach all respondents in order to update their contact information. If they could not be reached over the phone, we attempted to find them in person by going to their home area. In 2017, 9 years after the start of the study, we were able to reach and interview, in phone or in person, 95.4% of our study sample in a few months. In 2019, 11 years after the baseline, the tracking rate was 96.4%. This is remarkably low attrition for a longitudinal tracking of this kind. Other successful examples of longitudinal tracking in developing countries have achieved 81% retention over three years (South Africa; Lam, Ardington and Leibbrandt, 2011), or 95% (at the household-level) over five years (Indonesian Family Life Survey; Thomas, Frankenberg and Smith, 2002). Studies that deal with attrition by doing intensive tracking on a random subset of the "hard to find" subsample and then reweigh have obtained only 91% over seven years (Kenya; Duflo, Dupas and Kremer, 2015) and 84% over ten years (Kenya; Baird et. al 2017). Attrition is not differential by treatment group until 2017. During the 2019 survey round, the refusal rate increased from 1% to 2.5% in the control group, while it remained unchanged in the treatment group. This generates a small discrepancy in survey rates across arms, driven by males: male scholarship winners were 2.6 percentage points more likely to be surveyed than non-winners, on a basis of 93.1%. The non-winners who refuse the survey appear somewhat negatively selected,[17] suggesting that this differential attrition may if anything lead us to underestimate treatment effects for males when we focus on the 2019 wave.

4.3.4 Detailed In-Person Follow-up Survey (2013)

A detailed in-person follow-up survey was conducted from April 2013 to August 2013. For many study participants, this follow-up survey falls in the gap year between the end of secondary high school in July 2012 and potential enrollment in tertiary education in September 2013. The survey included modules on schooling, occupation, cognitive skills, labor market expectations, reproductive health and fertility, as well as attitudes and values, among other things. Most of these modules were fairly standard

[17] Regressing the 2017 value for "total years of education" on "refused 2019 survey" yields a coefficient of -1.64 (p-value=0.03). For "total earnings in the past 6 months" the coefficient is -662 GHX (p-value 0.15).

modules adapted from well-known surveys such as the Demographic and Health Surveys or the World Value Survey.

The only module we had to develop is the cognitive skills module. It included reading comprehension questions, as well as applied math questions (e.g. profit calculations, reading and interpreting a bar chart, etc.). There were 17 questions, modeled on the OECD PISA (Program for International Student Assessment) exam, tailored to the Ghana context by the research team with inputs from the Assessment Services Unit (ASU) of the Ghana Ministry of Education.

4.3.5 Callback Surveys (2015, 2016, 2017 and 2019)

Three yearly callback surveys were conducted to update respondents' contact information. Starting in 2015, the callback survey included about 30 minutes of questions on major life outcomes, specifically: tertiary education, fertility, partners, labor market activity, as well as year-specific questions (e.g. in the 2017 callback we asked about voting behavior in the presidential election of December 2016).

We have data on many outcomes and over multiple years, which raises the issue of multiple inferences. We deal with this by constructing summary indices and by presenting in Table A5 the sharpened q-values controlling for the false discovery rate (the expected proportion of rejections that are Type I errors) for p-values below the 0.1 threshold (Benjamini, Krieger, and Yekutieli, 2006).

4.4 Characteristics of Study Sample

Table 1 presents some summary statistics on the study sample. This data comes from baseline surveys administered to the respondents, as well as their guardians, in Fall 2008. As a test for balance, we show mean differences across groups for a battery of outcomes. Specifically, we run regressions of the form:

$$Y_i = \alpha_i + \beta T_i + \varepsilon_i \qquad (1)$$

where Y is the outcome of interest and T is whether or not the student won a scholarship. Since randomization was at the individual level, we do not cluster the standard errors. For each variable of interest, we show $\hat{\beta}$, the difference between the treatment and control group and its standard error. We also present the mean outcome in the control group. We show the means and estimate the regressions overall in column 1, and by gender in columns 2 and 3.[18] We show the results with region fixed effects and a control for junior high school finishing exam (BECE) score. The results do not change when controlling for the stratification variables (district, senior high school of admission, and student type dummies) and/or other important baseline characteristics.

Students were on average 17 years old at the onset of the study. Women are not older than men on average despite the fact that 27% of the female sample comes from the 2007 BECE cohort. This may suggest that male students are more likely to repeat grades, while female students who fail to be promoted drop out, so in a given class boys are more numerous and older than women. The mean score on the junior high school finishing exam (BECE) was 62% for girls and 63% for boys.[19] Our study participants come from poor households, which is unsurprising given that they are drawn from the financially constrained. Over 40% of the students lived in households with no male head. Approximately 9% of household heads in the sample had only some primary education, about 40% had been to junior high, and about 13% had some secondary education. Under 4% reported having any higher education, like university or vocational school.

Respondents had extremely optimistic beliefs about the returns to secondary education at baseline: the average perceived percentage increase in earnings if one completes senior high school compared

[18] Characteristics are also balanced across major-gender group (results were shown in earlier versions and are available online or upon request).

[19] Mean BECE performance on four core subjects: Math, English, Science and Social Studies. We rescaled the score on a 0-100% scale, 100% being a perfect score.

to not completing senior high school was 276% in the control group (Table 1). These high expected average returns are not driven by outliers: 46% thought the returns would be at least 100%.

Figure A1 shows that respondents saw a secondary school degree as the returns gateway to a government job. Over 70% thought they would be a government employee or in a profession dominated by government employees by the age of 25 if they completed senior high school (81% of females and 65% of males). In particular, respondents often thought they would be a teacher or a nurse, which may be because these are the most ubiquitous types of permanent wage employees with which our rural sample interacts.

4.5 The Macroeconomic Context, and recent policy changes

Before turning to the results, it is important to point out that the effects we measure should be interpreted as conditional on the macro-economic context at the time. Our study participants began senior high school in the 2008/2009 academic year at the earliest. Most participants who completed senior high school did so and entered the labor market in July of 2012, and our last follow-up survey was administered in 2017. Ghana had strong macro-economic performance through the first quarter of 2012, when GDP growth reached an all-time high of 25.0%, but between 2012 and 2016, GDP growth fell each year, reaching a fifteen-year low of 3.6% in 2016. It rebounded in Q2 of 2017 and has been strong since.

The government changed their secondary and tertiary education policy during our study period. Starting with the school year 2009/2010, the government shortened the length of senior high school from 4 years back to 3 years (what it was before 2007). Our study participants were thus the last cohort (2008/2009) enrolled in the four-year program. As a result, most of our participants graduated in a double cohort with the students who had enrolled a year later. Finally, in 2013, the government also changed their policy in nursing and teacher training programs. Between the 1980s and 2013, the government paid allowances large enough to cover all fees to all students enrolled in such programs, making them effectively fully subsidized for those admitted, and admissions in the programs were capped via a quota system. Both the allowances and the quotas were removed in 2014, taking into effect for the school year starting in September 2014. This was a year after the earliest date at which our study cohort could have enrolled in tertiary education—they graduated from senior high school in June 2012 and the earliest they could have applied for tertiary was Fall 2012 for a September 2013 start – but given the quotas, having to wait at least two years before getting admission was common, and so de facto the reform directly affected our study cohort. The government that was elected in December of 2016 brought back the allowances and quota system in August 2017.[20]

Government policies affecting the labor market also began to shift in 2012. In 2008, the government wage bill was 11.3% of GDP, which was the highest of the 12 West African countries surveyed by the World Bank. The Ghanaian government enacted a new salary scale for government employees in 2012, which raised government wage bill by 38% in one year (IMF, 2012). In 2015, the ballooning wage bill forced the Ghanaian government to accept an IMF loan. As a condition of the loan, the government was required to impose a net hiring freeze on government employment outside health and education departments. The net hiring freeze ran through most of the period in which we collected data and ended in April 2019.

5 Impacts on Educational Attainment

This section presents effects on educational attainment and skills. Section 5.1 discusses effects on secondary education. Section 5.2 discusses the effect on tertiary education. Section 5.3 provides a back

[20] http://3news.com/well-consider-increasing-teacher-trainee-allowance-to-ghc500-govt/

of the envelope estimate of the fiscal costs of a free secondary education policy.

5.1 Secondary Education

Considerable evidence suggests that participation in primary school is responsive to school fees, but less is known about how secondary school participation respond to fees, although the conditional cash transfer literature touches upon the elasticity with respect to opportunity cost.[21]

We estimate the impact of the scholarship on educational attainment using regressions similar to equation 1. In the specifications reported in the text, we include regional fixed effects, a mean junior high school finishing exam score and whether the junior high school finishing exam score is missing, though all our results are robust to the inclusion of baseline controls. The results are presented in Figures 1 and 2 and Table 2.

Seventy-five percent of scholarship winners enrolled in senior high school immediately upon learning about the scholarship, almost four times the enrollment rate in the comparison group (Figure 1). By 2017, 71% of the scholarship winners had completed senior high school, compared to 44% of the non-winners (Table 2). Thus, while many of those in the control group were eventually able to enroll, scholarships generated a large gap in educational attainment between winners and non-winners.

While the scholarship increased attendance in senior high school, it led to a small reduction in attendance in technical and vocational institutes (TVI). In the comparison group, 3.1% completed

[21] Cardoso and de Souza (2008), Glewwe and Olinto (2004), Gertler (2004), Ferreira, Filmer and Schady (2009) find fee reductions or conditional cash transfers (CCTs) increase primary enrollment. Barrera-Osorio, Linden, and Urquiola (2007) find fee reductions increased primary enrollment but find no effect on secondary enrollment. Angrist, Bettinger and Kremer (2006) find that vouchers for private secondary school increased completion rates. Barrera-Osorio et al. (2011) find effects of CCTs on secondary enrollment. Khandker, Pitt and Fuwa (2013) find that a stipend for secondary education increased enrollment among girls but had no effect among boys. Blimpo et al. (2019) find that secondary school fees elimination increased girls' enrollment by 55%.

TVI as of the 2019 survey. In the treatment group, only 0.7% had done so.

The scholarship increased senior high school completion rate from 40% to 68% among women (a 69% increase) and from 50% to 78% among men (a 56% increase) (see Table 2). The larger impact for women in percentage terms is consistent with Proposition 2, though the difference in treatment effects between genders is not significant. The lower absolute level of completion rate among women is primarily driven by the fact that about 28% of the women in the sample had completed junior high school one year prior to the scholarship program (the BECE '07 girls). Among those, take-up of the scholarship was significantly lower, at 56%, compared to 72% among women who had graduated in 2008 and 79% among men who had graduate in 2008 (see Figure 1).

The effect of scholarships on SHS completion is large irrespective of the type of school, initial performance and region (see Figure 2). In particular, the treatment effect is statistically significant at the 1% level at all quantiles of the initial test score distribution, and evenly spread throughout the distribution.

5.2 Tertiary Education

As of 2019, 15.2% of the comparison group had ever enrolled in tertiary education (5.8% at university, 4.0% at teacher training colleges, 2.4% at nursing colleges, and the rest at other professional schools. The treatment effect of the scholarship was an increase of 4 percentage points (26%) (Table 2), seen across all types of tertiary programs. This translates into a 3.5 percentage points (+40%) increase in the likelihood of having completed tertiary.

One caveat is that gaps of multiple years between senior high school and tertiary education are not uncommon in Ghana, so we may not yet be able to observe the full long-run effect of scholarships on tertiary education. As of 2017, a non-trivial share of the youth in the sample was still in the process of obtaining tertiary education, with over a third planning to apply, either to a professional program or as a mature student to the university (Table A2, Panel A). Such plans were significantly more common among scholarship winners. By 2019, however, very few had applied as mature students, and this was not significantly higher for scholarship winners. Over a third of the sample still expects to apply to tertiary in the future–and the gap between scholarship winners and non-winners remain very large. Whether this is pure wishful thinking or not is difficult to assess, but it seems likely, since by 2019, only about 5% of the comparison group and 6% of the treatment group were currently enrolled in tertiary education (Table 2), suggesting that very few of the 2017 tertiary aspirants succeeded in their tertiary plans.

The tertiary enrollment results conceals important heterogeneity by gender. Treatment effects on tertiary education are concentrated among women. Female scholarship winners are 7.4 percentage points more likely to have ever enrolled in a tertiary institution on a base of 12.2%, and 4.0 percentage points more likely to have completed tertiary on a base of 7.8%, while the effects on males are small and insignificant. Note that the effect on women is large enough that provision of free secondary education led to equalization of the rates of tertiary attendance by gender within our full sample. We do not see this full equalization for other outcomes, such as senior high school completion. Ghana has some gender quotas at the tertiary level, so these tertiary results should be interpreted bearing in mind this context.

The results so far suggest that marginal students (those induced to complete senior high school by the scholarship) struggle to move from senior high school completion to tertiary enrollment relative to infra-marginal students (those who could finish senior high school without a scholarship). Even if we assume that the entire treatment effect on tertiary enrollment is concentrated among marginal students, we find that only 15% of those induced to complete secondary school by the scholarship went on to tertiary education compared to 34% of the inframarginal students. This is not because marginal students are drawn from a lower part of the initial score distribution (compliers have similar BECE scores than always takers—we discuss this in Appendix B). One possible hypothesis is that since tertiary education costs more than secondary education, and subsidies for tertiary education (especially vocational teaching and nursing colleges) were cut back during our study period, students who were financially constrained at the senior high school level were financially constrained at the tertiary level. Marginal women, however, are much more likely to move on to tertiary than marginal men (29% vs 2%). This gender gap is consistent with Proposition 3 of the model, and could be read as supporting the hypothesis that most males who could make it to tertiary education are already being supported to enter senior high school by their families, but that the same is not true for females.

Overall, as of 2019 the scholarship had led to a 1.23 year increase in total years of education on average (Table 2). Quantitatively, the change is mainly concentrated in years spent in secondary school. Our reduced form estimates thus likely pick up to a large extent the change in time spent in secondary school (Angrist and Imbens, 1995).

The last row of Table 2 shows current enrollment status as of our last survey wave (2019). Scholarship winners are more likely to be enrolled in formal study – this is driven entirely by females, who are 3.2 percentage points more likely to still be studying, on a base of 4.1%, a very large gap in percent terms. This has implications for the estimates of labor market impacts, something we discuss in detail in Section 7.

5.3 Estimating the Fiscal cost of Free Secondary Education

Knowing the responsiveness of secondary school participation to school fees sheds light on the fiscal cost per additional year of enrollment from making secondary education free. Given the findings above, and the distribution of junior high school exit exam scores, we estimate that in the absence of incentive effects on primary school students, making secondary education free could require paying for 15 years of secondary school for every additional year of education generated by marginal students. To see the logic, note that on average, scholarship winners spent 3.08 years in senior high school, while non-scholarship winners spent 1.83 years in senior high school, a difference of 1.25 years. Therefore, the scholarship paid for 3.08 years of education for each 1.25 additional years of education. With a few assumptions, we can estimate the effect of a nation-wide free senior high school policy using these results. We assume (very conservatively) that the 80% of qualified students who enroll in senior high school nationwide in Ghana (Ajayi, 2014) would complete senior high school with or without financial help, and that the 20% of qualified students who do not enroll in senior high school behave like our sample.[22] With these assumptions, we calculate that a free senior high school policy would pay for 15.54 years of schooling for each additional year of schooling attained and the fiscal cost per additional secondary school graduate would be approximately $7,140.[23]

Note, however, that the promise of free secondary school for students who pass the junior high school finishing exam may incentivize more financially constrained students to study harder, allowing more of them to pass the exam and qualify for senior high school (for some evidence of such incentive effects, see Kremer, Miguel and Thornton (2009) at the upper primary level in Kenya, and Lajaaj, Moya and Sanchez (2018) at the tertiary level in Colombia.) In Ghana this is likely an important margin, since as of 2014 only about 40% of those who start junior high school pass the finishing exam (see footnote 4). However, even if one makes quite generous assumptions about the extent to which primary school students would be incentivized to work harder to pass exams, the ratio of infra-marginal to marginal students is likely to be fairly high. For example, if one assumes that the promise

[22] Since senior high school in Ghana now lasts three years instead of four, we also assume that the 20% of qualified students who do not enroll would attend 75% of the years spent in senior high school of our sample with the same ratio of infra-marginal to marginal years, and that full scholarships have the same effect on senior high school completion rates irrespective of how long senior high school is.

[23] Cost of the scholarship ($400) divided by expected additional graduates from one scholarship (which is the estimated treatment effect of a 26.3% increase in graduates multiplied by 20% of qualified students who do not enroll).

of free secondary education would lead one quarter of students who currently do not pass the primary school leaving exam to pass the exam, the ratio of years of education paid for to marginal years of education would fall from 15 to 6.

Targeting scholarships to students with lower senior high school attendance, and lower incomes, and targeting females could increase the ratio of marginal to infra-marginal expenditure and reduce any regressive effects of scholarships for senior high school.

6 Knowledge, Skills, Behavior and Fertility

Some have expressed concern about whether increases in access to education will lead to increases in learning, given the quality of schools (Pritchett, 2001). Knowledge and education are correlated in non-experimental data, but this may reflect the correlation between existing skills and enrollment. In this section, we document significant improvement in cognitive skills.

6.1 Learning Outcomes

Impacts on cognitive skills and knowledge are presented in Table 3. These results are based on oral tests administered as part of the 2013 in-person survey. Thus, these tests provide the effect after most study participants had completed or stopped going to senior high school but before participants had a chance to enroll in tertiary education.

Overall, scholarship winners score 0.143 standard deviations higher on the reading test, 0.125 standard deviations higher on math tests and 0.157 standard deviations higher overall. The point estimates are larger for female (0.192) than for males (0.112), especially in math, although the differences are not statistically significant. Note that there are very large differences in scores by gender in the control group, with men vastly outperforming women. Thus, despite very large gains, female scholarship winners are barely on par with male non-winners and far behind male winners in learning outcomes.

Learning gains are not simply due to winners trying harder on the test. We can show this in two ways. First, we find no differences between winners and non-winners on measures of IQ (Raven's matrices and digit span), which are supposed to not depend on education but obviously depends on effort or concentration (Table A2 Panel B). Second, at the time of the survey we had surveyors assess whether the respondent gave full effort on the test. Winners were 5.0 percentage points more likely to give full effort than non-winners (Figure A2). Within the comparison group, giving full effort is associated with a 0.69 standard deviations higher test score than not providing full effort. Since cognitive ability and effort on a test are likely to be positively correlated, this should be an overestimate of the effect of effort. Even if we assume this estimate is unbiased, it would imply that only 23% of the treatment effect comes from differences in effort. Interestingly, Figure A2 also shows a significant gender gap in effort provision on the test (Panel B): women were 11 percentages points less likely to be rated as providing full effort (it was often harder for them to concentrate due to the presence of small children). Under the assumption above, only 21% of the very large (0.35 std. dev.) gender gap in performance in the control group would come from differential effort, however.

Besides impacts on cognitive skills, we also find significant impacts on general knowledge: scholarship winners scored higher on a series of questions related to current political affairs (both national and international – the specific questions are listed in Table A3).

6.2 Connectedness and Technology Adoption

Table 3 also presents results on the adoption of technologies that may be useful for youths as they go on with life. Looking first at connectedness, scholarship winners are significantly more likely to engage with the media and to know how to use the internet as of 2013. Four years later, they score higher on an ICT/Social media adoption index (see components in Table A3), though the effects are driven by women, who are at a big disadvantage to start with (-0.23 standard deviation). The scholarship appears to help close this gender gap. Regular internet usage remains higher for the treatment group in 2019.

Turning to other technologies, we find that the scholarship accelerates adoption of bank accounts among women – here again, helping reduce the gender gap. We do not see any significant effects on adoption of agricultural technology despite a large gender gap there as well: we see no effect of the scholarship on fertilizer use for those involved in farming. Finally, we see no impact of winning the scholarship on migration to urban areas.

6.3 Health Behavior, Fertility, Child Health and Household

Table 4 presents results on health and fertility outcomes. Looking first at attitudes towards health, we find that winning a scholarship leads to safer health choices. Overall, scholarship winners adopt less risky (self-reported) sexual behavior (-0.047 SD on an index of 12 questions presented in Table A3) and more preventative health behaviors (0.105 increase on an index questions on three behaviors: hand-washing with soap, anti-malarial bed net use, and mosquito repellent use).

The impacts on self-reported sexual behavior are significant only for men, but for women we observe a decline in pregnancies and unwanted pregnancies, arguably a better measure of risky sexual behavior than self-reports. Indeed, scholarships dramatically changed women's fertility. By 2013, women in the scholarship arm were 6.6 percentage points less likely to have ever been pregnant (on a basis of 48.3% in the control group). Because the great majority of first pregnancies are reported to be unwanted, the fertility decline is almost exclusively a decline in unplanned, out-of-wedlock pregnancies. As shown in Figure 4, the fertility effect is sustained until our most recent survey, with a significant 0.15 fewer children (on a base of 1.3) born to women in the treatment group as of 2019.

Figure 5 shows that the hazard of pregnancy among scholarship winners remained lower among the treatment group even after the majority had completed their secondary education (2013 and onwards). These results are consistent with the results of a previous randomized experiment that reduced the cost of access to upper primary school in Kenya and found that the onset of childbearing was also delayed, with no-catch up in the two or three years following school exit (Duflo, Dupas and Kremer, 2015).

The finding that the gap in childbearing between treatment and comparison groups persists once the majority of scholarship winners are *out of school* suggests that the mechanism is not an "incarceration effect," preventing fertility for a few years while in school (Black, Devereux and Salvanes, 2008). We have collected data that sheds light on the importance to our respondents of the mechanisms most discussed in the literature, namely (1) increase in the opportunity cost of bearing and raising children (Becker, 1991); (2) the ability to make better choices thanks to better decoding of information (Rosenzweig and Schultz, 1989); (3) changes in desired fertility and (4) changes in the type or preferences of the partner.

Consistent with channel (1), we find and will show below that female winners are more likely to have contract employment than female non-winners, which presumably increases the opportunity cost of a child. And consistent with channel (2), we find large increases in learning for both men and women, and an increase in the adoption of preventive health behavior, as discussed above. There is no evidence for channel (3) in our sample (see Table 5). Finally, we find significant effects on partners. First, fertility changes coincide with changes in co-habiting behavior. By 2016 (age 25 on average), treatment women were 7.8 percentage points (23% of the control mean) less likely to have ever lived with a partner. This effect has mostly disappeared by 2019 however, unsurprisingly since by age 28 the great majority of both men and women report being married or cohabiting. The type of partners is however differential across groups: female scholarship winners are significantly more likely to have partners with tertiary education (+7.2pp on a basis of 19.5%).

The opposite is true for men: while only 7.2% have a partner who has tertiary in the control group, this reduces further by a significant 4.8pp in the treatment group. Besides this impact on partner characteristics, we see few changes in fertility and marriage behavior for men, although it is worth noting that men marry later and that parenthood is likely measured with much more error for them: since many pregnancies are out of wedlock and not all of them lead to shotgun marriages, it is possible that male respondents under-report births they may have been responsible for. One clear impact on male scholarship winners is that they are more likely to still be living with their parents, which may influence their labor supply decision.

6.4. Civic Participation

An outstanding question concerns the impact of education on civic engagement. Across OECD countries, voter turnout appears to have decreased over the past fifty years despite rising education levels (Wattenberg 2002, p. 28), questioning the long hypothesized causal effect of education on engagement. Experimental evidence at the micro-level is rare. Our data collection period spanned two presidential elections (held every 4 years) and two district assembly elections. We present results on voting behavior in Table A2 panel C. We find no effect of the scholarship on voting propensity, whether in presidential elections, where the turnout is very high overall, or in district assembly elections, where the turnout is much lower. This is in direct contrast with the findings in Sondheimer and Green (2010), who exploit three small-scale randomized education programs in the United States to study long-run impacts on voting behavior, and found large positive impacts from education to voting.

7 Labor Market

This section discusses the labor market impacts, through the lens of the model from Section 3. We focus on our two last rounds of data (2017 and 2019), as the long-run follow up is critical to capture the effects on public sector employment, which requires tertiary education and often a waiting period.[24] Indeed, recall from Section 5 that throughout most of our labor market survey period (2015-2019) there is entry and exit from tertiary. All of these are significantly more likely in the treatment group, which means that selection into the labor market is differential across arms, and differential across years within arms. Labor market outcomes could also be differential based on completing tertiary education, which is more likely for treatment students.

7.1 Sector of Work

Impacts on sectoral choice are presented in Table 5. Recall from Proposition 1 that we expect the highly skilled to try to shift into the premium sector if they have tertiary education, and to move away from self-employment otherwise. We find evidence for these two sectoral shifts. As of 2017, scholarship winners were 3.2 percentage points more likely to be public sector employees (more than a 100% increase given a low basis of 2.6% in the comparison group) and 5 percentages points less likely to be self-employed. By 2019, female scholarship winners remain 3.8 percentage points more likely to be public service employees (on a basis for 4.8%) and male scholarship winners are 2.6 percentage points more likely to be waiting for a public post assignment (typically as teacher or nurse in a public facility), on a base of 2.4%.

[24] All graduates of Ghanaian tertiary institutions are required to serve one year in the National Service. In the National Service, the graduate will work (usually for the government, but occasionally for a private company) for a year and receive a monthly stipend from the government. See https://nss.gov.gh/nss-faqs

Scholarship winners are no less likely to be self-employed by 2019, but the type of self-employment has shifted: as shown in Panel B, self-employed women are less likely to be involve in petty trade e.g hawking) and services (e.g. hairdresser), and more likely to be involved in a more formal enterprise (e.g. running a franchise store for a large company or doing wholesale trading). Male scholarship winners are significantly less likely to work in construction or transport, two sectors with significant occupational hazards, and more likely to work in services.

7.2. Labor Supply

Table 6 shows how these sectoral and industry shifts translate into differences in labor supply and compensation. For men, we find a large and significant decrease in working hours as of 2019. This is driven by an intensive margin effect (employed men working fewer hours), not a decrease in the probability of working. This suggests that the shift from construction/transport to services was accompanied with a reduction in over-time hours. We do not see any difference in hours across scholarship winners and non-winners for women. Obviously, a key margin of effort (intensity of work during official work hours) is not captured in our data, so we cannot directly test Proposition 1 (a) on the level of effort in the civic sector being set to 0.

7.2. Earnings

We show impacts on earnings in Panel B of Table 6. Consistent with proposition 4, we do not see evidence of increases in earnings despite the increase in tertiary education and public sector employment in the treatment group. Public sector wageworkers in our sample earn 3,335 GHX in 6 months on average, which is above the 85th percentile of the sample's earnings distribution. However, a quantile regression finds no effect of the scholarship on the 90th percentile of earnings. This is because the wages of the public sector wageworkers are offset by the control group having more self-employed in the higher deciles of earnings (Figure 5). The negative effect of the scholarship on self-employed entrepreneurs in the top decile of earnings is potentially consistent with the model in Section 3 where the scholarship helps high-ability workers attain government jobs where they earn a fixed wage and do not need to give any effort, while high-ability workers without a scholarship end up in the private sector where they need to exert more effort but can potentially have higher earnings.[25]

Hourly earnings are not higher in the treatment group despite higher education levels. This could be because scholarship winners have less work experience since they entered the labor force later. If education and experience are complements, then one might expect earnings to rise more in the treatment group over time. Alternatively, this could be due to differential reporting of work hours.

Overall, our confidence intervals for the earnings variables are very wide and we cannot exclude either zero effect, negative or large private returns. In Ghana many people work in agriculture or are self-employed and hence their income is subject to stochastic shocks and seasonal fluctuation. Moreover, for the self-employed income is highly subject to measurement error.[26] Finally, income is highly skewed. This makes it hard to pick up changes without very large samples. (Using log income as the dependent variable can help address the skewness, but this method is problematic in this setting where many report zero income. Another approach is to look at the inverse hyperbolic sine of income, but this amounts to a fairly arbitrary way of aggregating the increase in earning positive income and the smaller increase in log income conditional on positive income, so we prefer to avoid this method.)

[25] This could also be a mechanical effect of the fact that more control group members are self-employed, and self-employed have more variable and less precisely reported income—a large sample would mechanically increase the top incomes in this group. However, there is weak evidence that the control group are more likely to be in the top decile even conditional on being self-employed (though the coefficient is lower and the p-value =.12.

[26] Earnings from self-employment are likely measured with error as respondents may not be isolating the part of their business revenue that is true income for their household.

An alternative outcome of interest is the report financial well-being of respondents. In both 2017 and 2019 we asked whether people have a means to cope with an emergency that requires 200 GHX urgently (about $50). We create a financial insecurity dummy equal to 1 if respondents declare they would not be able to cope with such an emergency. We see no difference in this outcome across groups in 2017, but by 2019 there is a significant reduction in financial insecurity for females.

Bounds

Given that as of 2019 there is still a gap in formal study enrollment between scholarship winners and non-winners among women, all the effects discussed above may underestimate the causal impact on labor market outcomes for women who were not induced to go on to additional formal study/training. This would be the case if the students in the treatment group who were in formal study/training due to winning the scholarship would have had more positive labor outcomes than average had they not been in school. Upper bounds for the effect of the scholarship on earnings, constructed following Proposition 5 and as suggested in Section 3.3, are shown in Table 7. We estimate very large upper bounds for earnings.

7.3 Aspirations or Frustration?

While substantial in percentage terms, the increase in tertiary education and in obtaining public sector jobs was much lower than parents or children anticipated at baseline. Given this, one question is whether the program generated disappointment and frustration in the years that followed secondary school graduation, especially for males. This does not appear to be true on average, although the evidence does not point towards a large positive effect either: a satisfaction index (covering life satisfaction, financial satisfaction and a comparison of their life to others) shows a small insignificant negative treatment effect, as does a mental health index (Table A2 Panel E). Scholarship winners are as likely as non-winners to think that they can change their life, and that their life is as good as that of others. A striking result is that, in 2017, among those who have a job, scholarship winners are much less satisfied with it (a decline of -0.244 on a scale that ranges from 1 to 5, SE: 0.079), but also more confident they can get a better one (an increase of 0.071 on an index that ranges from 1 to 5, SE: 0.033). By 2019 satisfaction with one's job remains lower in the treatment group, and scholarship winners are significantly more likely to be actively looking for a job, whether or not they are currently employed, suggesting that they maintain higher aspirations.

Thus, overall, access to free senior high school does not appear to be associated either with deep frustration or significantly happier lives. Although few graduates have found the jobs that meet their high expectations for education at baseline, their hopes appear to be still alive.

8 Comparison between IV estimates, OLS and ML-debiased OLS

The effects of free education are of considerable interest in their own right, but they may also shed light on more general issues of the impact of education. In Appendix C, we argue that non-educational channels of scholarship effects are likely to be small, and that while exclusion restrictions are probably not literally satisfied, instrumental variable estimates of the effect of education based on using random assignment of scholarship receipt are likely to be reasonable approximations of the causal effect of education. This section computes IV estimates, compares them to the OLS, and tests whether the IV estimates can be recovered through recent new non-experimental machine learning techniques.

For the IV, we assume that net non-educational effects and effects on infra-marginal applicants can be neglected, and estimate:

$$y_i = a_i + \beta S_i + \varepsilon_i \qquad (2)$$

where S_i is the number of years of education for individual i and y_i is the outcome of interest. We use winning the scholarship as an instrument for years of education. This estimates the local treatment effect of education on compliers. It is therefore of interest to know how compliers compare to always-takers in background characteristics. Table A5 shows the difference in background characteristics between treatment and control groups, *among those who completed senior high school*. Interestingly, we find no difference in the junior high school exit exam score, suggesting that compliers and always takers were performing equally, and confirming the premise that ability to pay fees is the key barrier to enrollment for compliers.

Table 8 reviews the OLS and IV estimates of the returns to education for our key outcomes: test scores, fertility, health behavior, sector of employment, earnings. The OLS estimates are based on the control group only. The IV estimates use the full sample and instrument years of education with the randomized scholarship treatment assignment. We present the OLS results without any controls, the OLS results controlling for BECE score, and the IV. The OLS estimates are at times higher (educational attainment, learning) and at times lower (earnings, preventative health behavior) than the IV estimates of the returns.

There are two potential reasons why the OLS and IV estimates are different. First, the OLS results could be biased because those who self-select into obtaining secondary education have different characteristics that matter for outcomes later in life. Second, the OLS and IV estimate effects for different subgroups: the IV estimates the local average treatment effect on compliers (those who can only attend secondary education if they get a scholarship) while the OLS estimates effects for always takers. In this section, we perform a Lalonde (AER 1986)-type exercise to test whether we can recover the IV estimates from the control group with recent Machine Learning (ML) techniques. Specifically, we ask: can causal effects be recovered by controlling for the very rich set of control variables (over 1,000) that we collected at baseline?

To select from among the many available observables that can be used as control, we apply the Double Machine Learning method proposed in Chernozhukov et al. (2018). In a nutshell, the estimate works by using a random forest to flexibly partial out the effect of the baseline variable from the outcome variables and the education variable. We also present a version of the DoubleML estimate that weighs the observations by the heterogeneity in treatment effect in the first stage, in order to recover the effect on people who observationally look like the compliers. A finding that the "weighted DoubleML" estimate is close to the IV estimate would imply that any difference between the regular DoubleML and the IV are due to the fact that the IV recovers a different estimate, suggesting that the (unweighted) DoubleML may be a good estimate of the ATE on education.

The results suggest that, despite the wealth of control variables available, the machine learning estimates are generally quite close to OLS estimates, suggesting that the observed variables explain little of the underlying heterogeneity. For most outcomes, the weighted DoubleML estimate is closer to the IV estimate than the raw OLS estimate, but in most cases less than half of the gap is closed. For example, the OLS estimates of the effect of education on test scores (0.25 for females and 0.16 for males) is larger than the IV estimate (0.14 for females and 0.09 for males), perhaps reflecting a standard ability bias. The DoubleML estimate is only slightly smaller than the OLS estimate and the weighted DoubleML does not get closer to the IV. DoubleML and weighted DoubleML both do very poorly for most labor market outcomes, where their estimates are often farther from the IV estimates than the OLS estimates. Earnings per hour is the only labor market outcome where the DoubleML and weighted DoubleML estimates are in between the OLS and IV estimates.

Overall, the results suggest that despite the challenges and costs associated with longitudinal datasets, identifying other sources of experimental or quasi-experimental variation in educational attainment coupled with long-run follow up-data is going to be key to accurately measure the effect of secondary education. On a side note, it also suggests that continuing to stress-test the DoubleML approach by comparing experimental and non-experimental variation would be very valuable.

9 Conclusion

With primary school enrollment rates getting close to 100% in most countries, policy attention has shifted to secondary school. Ghana is a case in point, with the latest government having delivered in September 2017 on its campaign promise to make senior high school free. Yet very little is known on the causal impact of secondary education in developing countries.

Using a randomized controlled trial in which a random subset of qualified but financially constrained students in rural Ghana were awarded secondary school scholarships, and detailed outcomes data was collected over 11 years, we find that scholarships increase secondary school completion rates by 25 percentage points. Furthermore, we find that secondary education does impart significant learning gains, enable healthier behaviors, and delays fertility and marriage, in particular for women.

The scholarship also significantly increased enrollment in tertiary education at the time of our endline (after 11 years) from 15% to 19%. Despite the fact that scholarship winners were more likely to still be enrolled in school at the time of the survey, they were also more likely to be formally employed, and more likely to have public sector jobs and jobs with benefits.

We find more positive treatment effects for women relative to men along a number of dimensions, although given our small sample size these differences are not always significant on a variable-by-variable basis. Treatment effects for women are greater on learning, on tertiary enrollment, on public service employment, on fertility and marriage. One possible hypothesis is that some households are more inclined to send their sons to senior high school than their daughters absent scholarships, while others are already sending both sons and daughters, and therefore at the margin there are more girls who could benefit from senior high school but will not go in the absence of a scholarship than there are boys. Consistent with this, women have lower rates of senior high school secondary attendance in Ghana.

While scholarships increased the probability of tertiary education and obtaining a public sector job, the overall fraction of secondary school graduates attending tertiary education remains fairly low in this sample. Few of these secondary school graduates will meet their ambition of becoming teachers or entering other occupations requiring tertiary education and commanding high rents. To the extent that government jobs are in fixed supply, there will be excessive entry into competing for these jobs since entry creates a negative externality for other applicants. A symptom of this competition is that 64% of the treatment group (almost all of those who graduated from secondary school) had plans to attend tertiary, even if few have been able to carry those plans out (24% applied and 12% ever enrolled).

In the traditional human capital model, education imparts skills that should increase productivity in the labor market. We cannot reject the hypothesis that there is no such effect, although as we pointed out, it may be hard to detect with the data we have, and these results may change over time as those who have gone to tertiary school graduate and enter the labor market. Employment rates will likely rise in the rest of the sample. This will both increase all wages, and give us a larger and more representative sample to estimate any productivity impacts of education. Finally, as we noted, our sample graduated during a challenging macroeconomic time in Ghana, and in an environment where the market was flooded with new graduates. Overall labor market effects might have been more positive in other circumstances. Estimating the long-run returns to free secondary education will require surveying our study sample again in five or ten years. This underscores the importance of very long-term longitudinal follow up.

Unsurprisingly, if parameters are such that free secondary education increases welfare, voters will support it. However, data and theory also suggest reasons why voters might support free primary education even if labor market gains from education are entirely at the expense of others. If people are systematically overoptimistic about the chance household members will get premium sector jobs conditional on education (as our evidence suggests) and if they underestimate the extent to which others will increase education in response to free secondary education (as suggested by certain theory), then they may overestimate the extent to which they would benefit from free secondary education. Note also that to the extent that people overestimate the chance that members of their households will obtain premium sector jobs, they may be less inclined to support policies that reduce the rents associated with these positions.

One potential policy implication is that governments or others may wish to provide more accurate information. The huge discrepancy between stated expectations of the effect of secondary education and the estimated actual effect implies that it may be appropriate to inform students that those with low scores on the JHS exam have a low probability of entering tertiary education. Policy implications for subsidizing secondary education likely depend on the policymakers' welfare function. One potential policy that might be worth considering, which would not go as far as free senior high school education, would be to make senior high school free for students from poor families who score at the very top of the JHS exam. Under the model, the impact of expanding access to education on the quality of government work depends on how the skill of the average new person who qualifies for a government job does relative to the average of the current pool from which the government hires. It is easy to construct a situation in which expanding access to education actually reduces the quality of government hires. Awarding scholarships only to those who score very well in the junior high school leaving exam would increase the quality of government hires, and if government output is sufficiently sensitive to skill, this could yield an important benefit. Focusing on poor people presumably improves the ratio of marginal to inframarginal expenditure. Nonetheless, it seems the strongest case for further subsidizing secondary education is for girls. The fact that they are starting from such a disadvantaged situation, and the effect of learning outcomes, tertiary education, political awareness, health and fertility are large enough to make it worthwhile.

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Appendix A: Model Proofs

Proof of Proposition 1. (i) Given that the lower support of the shock in the skill production function is $\underline{\varepsilon} > \frac{(1+c_C)}{A_h} - f\left(1, \underline{a}\right) - \frac{\eta}{A_h}$, children's skill level will be at least $\frac{(1+c_C)}{A_h}$. With effort of 1, they can therefore earn at least $1 + c_C$ in self-employment sector. This ensures that they equalize the marginal utility from consuming good 1 to 1 and consume positive quantity of good 2 even if they pay to educate their children. They will therefore behave as if they are risk neutral.

(ii) The utility maximization problem faced by the children is:

$$\max_{\{e_i, x_i^1, x_i^2\}} \ ln\, x_i^1 + \ x_i^2 \ - \frac{1}{2} e_i^2$$
$$s.t.\, x^1 + x^2 \leq E[w]$$

Since this labor market is competitive, fixed costs in the competitive private sector are borne by the worker and hence expected wages in the competitive sectors are $E[w_h] = A_h s \ + \ e$ in self-employment and $E[w_p] = A_p s \ + \ e - f_p$ in the private competitive sector. In the premium sector, wage is fixed at $w_g = \ A_p s \ + \ \phi - f_p$. Solving the UMP gives rise to $e^* = 1$ in the self-employment and competitive private sectors and $e^* = 0$ in the premium sector, as (a) states.
Moreover, optimal consumption of good 1 is 1 for all three sectors and maximal expected utility are $E[u_h]^* = A_h s - \frac{1}{2}$, $E[u_p]^* = A_p s - f_p - \frac{1}{2}$ and $E[u_g]^* = A_g s + \phi \ - f_p - 1$ respectively.

(iii) A worker will therefore be indifferent between working in the self-employment and the competitive private sector if maximal expected utility is equalized, that is, $A_h s - \frac{1}{2} = A_p s - f_p - \frac{1}{2}$. Rearranging this gives the result in (b). Highly skilled workers with skill s> $\frac{f_p}{A_p - A_h}$ will prefer to work and be paid their marginal product in the competitive private sector to working in the self-employment sector while those with skill s< $\frac{f_p}{A_p - A_h}$ will choose self-employment. Highly skilled workers with skill s> $\frac{f_p}{A_p - A_h}$ and tertiary education will prefer to work in the premium sector because $\phi \geq \frac{1}{2}$ implies they receive a premium above their competitive private sector wage and because they do not face any effort costs. This gives the result in (c).

Proof of Proposition 2. (i) Substituting the budget constraints in the objective function, we have that the household with a wealth level $y_i \geq 1 + c$ will solve the following problem:

$$\max_{\{D_i, x_{i0}^1\}} \ ln\, x_{i0}^1 + \ y_i - c_i D_i - x_{io}^1 + \ \lambda_{ig}(E[w_i | D_i = 0] - \frac{3}{2} + \widehat{\Delta_i} D_i)$$

The first order conditions with respect to x_{io}^1 is $x_{io}^{1*} = 1$. This implies that the household with a wealth level $y_i > 1 + c_i$ will choose secondary education $D_i = 1$ if and only if

$$ln x_{io}^{1*} + y_i - c_i - x_{io}^{1*} + \lambda_{ig}\left(E[w_i|D_i = 0] - \frac{3}{2} + \widehat{\Delta_\iota} D_i)\right)$$
$$\geq ln x_{io}^{1*} + y_i - x_{io}^{1*} + \lambda_{ig}\left(w_{i|\boldsymbol{D}_i=0} - \frac{3}{2}\right)$$

This simplifies to $\lambda_{ig}\widehat{\Delta_\iota} \geq c_i$.

Households with wealth level $1 < y_i < 1 + c_i$ will have to choose between buying $x_{io}^{1*} = 1$, spending the rest on x_{io}^2 and buying education, spending the rest on x_{io}^1. Hence, $D_i = 1$ if and only if

$$ln(y_i - c_i) + \lambda_{ig}\left(E[w_i|D_i = 0] - \frac{3}{2} + \widehat{\Delta_\iota}\right) \geq ln1 + y_i - 1 + \lambda_{ig}\left(E[w_i|D_i = 0] - \frac{3}{2}\right)$$

This simplifies to $\lambda_{ig}\widehat{\Delta_\iota} \geq y_i - 1 - ln(y_i - c_i)$.

Households with $y_i \leq 1$ will be unable to consume in the region where their utility increases linearly, that is, they will be unable to consume any good 2. They will invest in secondary education if and only if:

$$ln(y_i - c_i) + \lambda_{ig}\left(E[w_i|D_i = 0] - \frac{3}{2} + \widehat{\Delta_\iota}\right) \geq ln y_i + \lambda_{ig}\left(E[w_i|D_i = 0] - \frac{3}{2}\right)$$

Rearranging this gives $\lambda_{ig}\widehat{\Delta_\iota} \geq ln y_i - \ln(y_i - c_i)$.

Therefore, the thresholds for choosing $D_i = 1$ by households with different wealth levels are:

(i) $\lambda_{ig}\widehat{\Delta_\iota} \geq c_i$ if $y_i \geq 1 + c_i$
(ii) $\lambda_{ig}\widehat{\Delta_\iota} \geq y_i - 1 - ln(y_i - c_i)$ if $1 < y_i < 1 + c_i$
(iii) $\lambda_{ig}\widehat{\Delta_\iota} \geq ln y_i - ln(y_i - c_i)$ if $y_i \leq 1$

Noting that $c_i = c_C$ if $T_i = 0$ and c_T if $T_i = 1$ with $c_C \geq c_T$ and the thresholds for $\lambda_{ig}\widehat{\Delta_\iota}$ are increasing in the cost of education, it is clear that households with $y_i \leq 1$ will face a lower threshold for choosing $D_i = 1$ in the treatment group compared to that in the comparison group. Further, in the absence of the scholarship, households with wealth level $y_i \geq 1 + c_T$ in the treatment group would have either had $y_i \geq 1 + c_C$ with a threshold of c_C, or they would have had $1 + c_C \geq y_i \geq 1 + c_T$ with a threshold of $y_i - 1 - ln(y_i - c_C)$, both of which are greater than c_T, the threshold that they now face. Hence, for any wealth level y, households in the treatment group will face a lower threshold for weighted NPV gain $\lambda_{ig}\widehat{\Delta_\iota}$ from choosing $D_i = 1$ than households in the comparison group. By differentiating the thresholds for households with $y_i \leq 1$ and $y_i \geq 1 + c_i$ with respect to y, one can also note that while the decision of secondary education is unaffected by income for the rich households with $y_i \geq 1 + c_i$, the poor households with $y_i \leq 1$ will find it relatively easier to meet the threshold for secondary education as their income rises.

(ii) We have that the reward from secondary education in NPV is

$$\widehat{\Delta_i}(s_i) = p_{is}\,[p_{ig}\left(A_p s_i + \phi + 0.5 - f_p - E[w_i|D_i = 0]\right) + (1 - p_{ig})(E[w_i|D_i = 1] - E[w_i|D_i = 0])]$$

Taking a derivative of $\widehat{\Delta_i}$ with respect to perceived ability, we get

$$\frac{\partial \widehat{\Delta_i}}{\partial \hat{a}_i} = p_{is}[\frac{\partial p_{ig}}{\partial \hat{a}_i}\left(A_p s_i + \phi + 0.5 - f_p - E[w_i|D_i = 0]\right)$$
$$+p_{ig}\left(A_p \frac{\partial s_{i|D_i=1}}{\partial \hat{a}_i} - \frac{\partial E[w_i|D_i=0]}{\partial s_i}\frac{\partial s_{i|D_i=0}}{\partial \hat{a}_i}\right)$$
$$+(1 - p_{ig})\left(\frac{\partial E[w_i|D_i=1]}{\partial s_i}\frac{\partial s_{i|D_i=1}}{\partial \hat{a}_i} - \frac{\partial E[w_i|D_i=0]}{\partial s_i}\frac{\partial s_{i|D_i=0}}{\partial \hat{a}_i}\right)]$$
$$+\frac{\partial p_{is}}{\partial \hat{a}_i}[p_{ig}\left(A_p s_i + \phi + 0.5 - E[w_i|D_i = 0]\right) + (1 - p_{ig})(E[w_i|D_i = 1] - E[w_i|D_i = 0])]$$

Since $\frac{\partial p_{is}}{\partial \hat{a}_i} > 0$ and $p_{is} > 0$, we only need to consider $\frac{\partial p_{ig}}{\partial \hat{a}_i}\left(A_p s_i + \phi + 0.5 - E[w_i|D_i = 1]\right) + p_{ig}\left(A_p \frac{\partial s_{i|D_i=1}}{\partial \hat{a}_i} - \frac{\partial E[w_i|D_i=0]}{\partial s_i}\frac{\partial s_{i|D_i=0}}{\partial \hat{a}_i}\right) + (1 - p_{ig})\left(\frac{\partial E[w_i|D_i=1]}{\partial s_i}\frac{\partial s_{i|D_i=1}}{\partial \hat{a}_i} - \frac{\partial E[w_i|D_i=0]}{\partial s_i}\frac{\partial s_{i|D_i=0}}{\partial \hat{a}_i}\right)$. Since $\frac{\partial p_{ig}}{\partial \hat{a}_i} > 0$ and $E[w_i|D_i = 0] = A_p s_i + 1 - f_p$ if in the private sector and $E[w_i|D_i = 0] = A_h s_i + 1$ if in the self-employment sector, the first term is positive.

This also implies that $A_p \geq \frac{\partial E[w_i|D_i=0]}{\partial s_i}$ and due to the complementarity between education and ability in the skill technology we have $\frac{\partial s_{i|D_i=1}}{\partial \hat{a}_i} \geq \frac{\partial s_{i|D_i=0}}{\partial \hat{a}_i}$. Hence the second term is also positive. Since $\frac{\partial E[w_i|D_i=1]}{\partial s_i} - \frac{\partial E[w_i|D_i=0]}{\partial s_i}$ is either zero if the sector of the worker is unchanged or it will be positive if a worker with $D_i = 1$ is in the competitive private sector while a worker with $D_i = 0$ is in the self-employment sector $\frac{\partial E[w_i|D_i=1]}{\partial s_i} \geq \frac{\partial E[w_i|D_i=0]}{\partial s_i}$. Along with $\frac{\partial s_{i|D_i=1}}{\partial \hat{a}_i} \geq \frac{\partial s_{i|D_i=0}}{\partial \hat{a}_i}$, this implies that the third term is also positive. Hence $\frac{\partial \widehat{\Delta_i}}{\partial \hat{a}_i} \geq 0$. By continuity there exists a threshold level of the estimate of child ability above which all households will invest in education which gives the result in (a).

(iii) All else equal, this threshold level of ability will be greater for households in the comparison group than the treatment group given the derivation in (i) of this proof. This yields the result in (b). Part (i) together with the assumption $\lambda_{if} \leq \lambda_{im}$ gives the result in (c).

Proof of Proposition 3. If all households are identical in wealth and if all households weigh boys' and girls' utility equally, all households will face the same ability threshold a^*. Education subsidies lowering the cost of education from c_C to c_T will lead all households to lower this threshold for ability given Proposition 2. Therefore, the marginal children getting education in response to this cost subsidy will have lower ability. This gives the result in (a). On the other hand, if there is heterogeneity in wealth and thus thresholds, it is possible that marginal secondary school students could have higher initial ability than inframarginal secondary school students. To see this, consider an extreme case in which there are two types of household with the same λ_{ig}: rich with $y_i > 1 + c_C$ and poor with $y_i < 1$. Suppose that $\lambda_{ig}\widehat{\Delta_\iota} = c_C$ for the rich households so that they send their children to secondary school whereas $\lambda_{ig}\widehat{\Delta_\iota} < lny_i - ln(y_i - c_C)$ for the poor households so that they do not send their children to school. For $y_i < 1$, $lny_i - ln(y_i - c_C) > c_C$, so we can further assume $\lambda_{ig}\widehat{\Delta_\iota} > c_C$, for the poor households. Then a subsidy of $\frac{y_i-(y_i-c_C)\exp(\lambda_{ig}\widehat{\Delta_\iota})}{\exp(\lambda_{ig}\widehat{\Delta_\iota})}$ which ensures that $\lambda_{ig}\widehat{\Delta_\iota} = lny_i - ln(y_i - c_T)$ for the poor households will induce them to send their children to school while leaving the decisions of the rich households unchanged. These marginal children will be of a higher perceived ability than the inframarginal children since $\widehat{\Delta_\iota}$ faced by the poor households is greater than that faced by the rich households and $\widehat{\Delta_\iota}$ is increasing in ability as shown in Proposition 2. This proves the result in (b).

Similarly, if households are heterogenous in their level of altruism for the child's welfare, with some caring more about their children, for example, because of preferences for boys, then the marginal children induced to secondary education may have higher ability than inframarginal children.

To see this, assume there are two types of households, household h with higher level of parental altruism for their child's welfare λ_h, l with lower level λ_l. Neither faces credit constraint, i.e., $y_h, y_l > 1 + c_C$. As $\lambda_h > \lambda_l$, it can be that $\lambda_h\widehat{\Delta_l} > \lambda_h\widehat{\Delta_h} \geq c_C > \lambda_l\widehat{\Delta_l}$, in other words household h send their children to secondary education, while household l whose child has higher ability does not. An education subsidy such that $\lambda_l\widehat{\Delta_l} > c_T$ will mean that marginal children induced to enroll in secondary education due to the subsidy will have higher ability than the marginal children. This proves (c). This also implies that if there is gender bias, with some households educating all girls in the absence of subsidies for education, but others only educating the highest ability girls, then the marginal girls induced into school by free secondary education may be higher ability than inframarginal girls.

Proof of Proposition 4. Denote the initial earnings conditional on being in the self-employment sector and competitive private sector respectively as $W_{hC} = \frac{\int_0^{\frac{f_p}{A_p - A_h}} (A_h s + e)\ dS_C}{\int_0^{\frac{f_p}{A_p - A_h}} dS_C}$ and $W_{pC} = \frac{\int_{\frac{f_p}{A_p - A_h}} (A_p s + e - f_p)\ dS_C}{\int_{\frac{f_p}{A_p - A_h}} dS_C}$ where S_C denotes the initial skill distribution in the control group. An education subsidy will lead to a skill distribution S_T in the treatment group that first order stochastically dominates S_C. The threshold of skill level above which workers prefer to work in the competitive private sector is s> $\frac{f_p}{A_p - A_h}$. This means that the upper tail - the top percentiles corresponding to skill level above this threshold - in the control group skill distribution is in the competitive private sector. Following the subsidy, the treatment group will have a skill distribution above this threshold that first order stochastically dominates the upper tail in the control group.

Suppose initially no one in the control group chooses $D_i = 1$ but have skill level s> $\frac{f_p}{A_p - A_h}$ so that they work in the competitive private sector. Then an education subsidy inducing $D_i = 1$ would lead workers to stay in the private sector and get higher earnings. This would lead earnings conditional on private sector employment to increase.

On the other hand, suppose S_C is such that there is only one highly skilled person in the competitive private sector and all others with skill level s< $\frac{f_p}{A_p - A_h}$ work in the self-employment sector. A subsidy that induces the low skilled workers to undertake secondary education and increases their skill level to just above $\frac{f_p}{A_p - A_h}$ will lower the earnings conditional on employment in the competitive private sector. This gives the result.

Proof of Proposition 5. In t=2, secondary graduates who do well enough in school continue to tertiary education while the rest join the labor market. Those who join the labor market will have the same earnings in t=3 as in t=2. Those who are in tertiary education in t=2 will earn more in t=3. Suppose a% of students in the comparison group will continue to tertiary education and obtain premium sector jobs. Under perfect randomization, the same proportion of students in the treatment group will obtain premium sector jobs regardless of the treatment. Additionally, now there will also be students who will only go to secondary education with subsidies, of which some will eventually end up in the premium sector. Hence the difference of earnings between the treatment group and the comparison group will be larger at t=3. This gives (a).

In t=3, high ability agents who secure premium sector jobs will reduce their effort and take part of their rents as increased utility as Proposition 1 shows. Therefore, comparing the difference in earnings conditional on employment between the treatment and control group will therefore underestimate the welfare effect. This gives rise to (b).

Proof of Proposition 6: The unconstrained social planner seeks to maximize total utility in the economy. Denote distribution of households by $\mathcal{H}$. The utility maximization problem of the unconstrained social planner can be written as:

$$\max_{\{D_i, x_i^1, x_i^2\}_{i \in \mathcal{H}}} \sum_{i \in \mathcal{H}} [ln x_i^1 + x_i^2 + (E[w_i | D_i = 0] - \frac{3}{2} + \Delta_i D_i)]$$

subject to $\sum_{i \in \mathcal{H}} (x_i^1 + x_i^2) \leq \sum_{i \in \mathcal{H}}(y_i - c_i D_i)$.

As we assume the economy is wealthy enough, every household consumes positive amount of good 2 in equilibrium. Moreover, the first order conditions give $x_i^1 = x_1^*$ for all households. For secondary education, the threshold is also the same for every child, which is $\Delta_i \geq C_c$. Those whose initial ability is higher than the threshold will be sent to the secondary education while others will be directed to the labor market.

Proof of Proposition 7: Suppose all households are homogenous, subject to the same level of imperfect altruism (i.e., $\lambda_i = \lambda < 1$ for all i) and none faces a credit constraint ($y_i > 1 + c_c$ for all i). Because the parents have full information on children's ability, $\widehat{\Delta_i} = \Delta_i$. As derived earlier, the threshold for sending their children to secondary education is $\lambda_i \Delta_i \geq c_i$. If $\lambda_i \Delta_i < c_i$ and $\Delta_i > c_i$, then the parents will not invest in secondary education while the social planner will. In this case, an education subsidy of $c_i - \lambda_i \Delta_i$ will induce this household to send their child to secondary education. A tax of the same size reduces the wealth of the household to $y_i - c_i + \lambda_i \Delta_i$, which after paying for the education at the new price $\lambda_i \Delta_i$ is still greater than 1 by our assumption. Therefore, this tax on the household income will only reduce the consumption of good 2 by $c_i - \lambda_i \Delta_i$ without influencing consumption of good 1. This in turn results in a reduction in utility of $c_i - \lambda_i \Delta_i$. However, for the children, the expected gain from secondary education is Δ_i, which is greater than its total cost of education that the parents now bear after the education subsidy: $c_i - \lambda_i \Delta_i + \lambda_i \Delta_i = c_i$, so this policy will increase total welfare. This proves the proposition.

Proof of proposition 8: Suppose there are two types of households in the economy: n_r rich households with $y_i^r > 1 + C_c$ for all $i \in R$, and n_p poor households with $y_i^p \leq 1 + C_c$ for all $i \in P$. As assumed in the beginning of this section, the economy is wealthy enough and on average households have wealth greater than $1 + C_c$, that is, $\frac{\sum_{i \in R} y_i^r + \sum_{i \in P} y_i^P}{n_r + n_p} > 1 + C_c$. Therefore, the social planner can raise taxes of $\sum_{i \in P} 1 + C_c - y_i^p$ in total from rich households, while leaving their after-tax wealth greater than $1 + C_c$. A lump sum transfer of $1 + C_c - y_i^p$ from rich households to each poor household will lift the credit constraint faced by poor households and, without any other distortion, increase their total welfare by at least $\sum_{i \in P} 1 + C_c - y_i^P$. The tax will therefore only reduce the consumption of good 2 from rich households by $\sum_{i \in P} 1 + C_c - y_i^p$, whose marginal utility is 1 while the marginal utility of good 2 for the poor household is greater than 1. Thus the transfer can be beneficial.

Proof of Proposition 9: From the perspective of the social planner, when workers in premium sector maximize their utility $ln x_i^1 + x_i^2 - \frac{1}{2} e_i^2$, they are subject to $x_i^1 + x_i^2 \leq Y_g = A_g s + e - f_g$ instead of $x_i^1 + x_i^2 \leq E[w_g] = A_p s + \phi - f_p$. Let $E[u_g^p]^*$ denote the maximal expected utility of premium sector workers. Solving the utility maximization problem gives $E[u_g^p]^* = A_g s - \frac{1}{2} - f_g$. Therefore, for the social planner, the net present value of sending a child to secondary education is

$$NPV^p|_{D_{i=1}} = p_{is}\left[p_{ig}\left(A_g s_i - \frac{1}{2} - f_g\right) + (1 - p_{ig})\left(E[w_{i|D_i=1}] - \frac{3}{2}\right)\right]$$

Hence the difference of NPV for the social planner is

$$\widehat{\Delta_\mathrm{i}^\mathrm{p}}(s_i) = p_{is}\,[p_{ig}\,(A_g s_i + 1 - f_g - E[w_{i|D_i=0}])$$

$$+(1 - p_{ig})(E[w_{i|D_i=1}] - E[w_{i|D_i=0}])]$$

We compare it with decentralized NPV difference

$$\widehat{\Delta_\imath}(s_i) = p_{is}\,[p_{ig}\,(A_p s_i + \phi + \frac{1}{2} - f_p - E[w_{i|D_i=0}])$$

$$+(1 - p_{ig})(E[w_{i|D_i=1}] - E[w_{i|D_i=0}])]$$

Calculate their difference $\widehat{\Delta\Delta} = \widehat{\Delta_\mathrm{i}^\mathrm{p}}(s_i) - \widehat{\Delta_\imath}(s_i)$

$$= p_{is}p_{ig}[s_i(A_g - A_p) + f_p + \tfrac{1}{2} - \phi - f_g]$$

If A_g is sufficiently greater than A_p such that $s_i(A_g - A_p) + f_p + \frac{1}{2} - \phi - f_g > 0$, then, compared with the social planner, households will have higher threshold of ability for sending their children to secondary education. This results in underinvestment in education, thus the social planner should use the net income of the premium sector $\sum_{\mathrm{i}\,\in \mathrm{g}}(Y_{ig} - w_{ig})$ to subsidize education and vice versa.

Proof of Proposition 10: Suppose all households are homogenous, face no credit constraint and have perfect altruism (i.e., $y_i > 1 + c_i$ and $\lambda_i = 1$). By assumption, $\widehat{\Delta_\imath} = \Delta_i + d$. Parents' decision for secondary education is subjected to this optimistic bias. Their threshold for sending their children to secondary education is $\widehat{\Delta_\imath} \geq c_i$, and therefore we have $\Delta_i > c_i - d$.

Consider households whose perceived ability of children is such that $\widehat{\Delta_\imath} \in [c_i, c_i + d)$ and thus $\Delta_i = \widehat{\Delta_\imath} - d < c_i$. Those are households whose educational decisions are distorted by this systematic overestimation. For a social planner who's aware of this systematic bias but also the fact that her estimation of children's ability can be worse than the parents, who overestimate the children's ability by constant *d,* will resort to using taxes in this decentralized economy. As the real benefit of secondary education for these households is Δ_i, while its cost is c_i, by taxing education by *d*, the social planner can stop them from sending their children to secondary education and thus increase their welfare by $c_i - \Delta_i$. For those with $\widehat{\Delta_i} < c_i$, they wouldn't have sent their children to secondary education even without the tax, so it will not influence their welfare. For those with $\widehat{\Delta_i} + d \geq c_i$, they will send their children to secondary education regardless of the tax. They suffer a loss of *d* from the increase in the cost of secondary education, but enjoy benefits from an increase in their consumption in good 2 because of the subsidy to their income of *d* such that budget balance holds. Therefore, their welfare is not influenced either.

Appendix B: Disaggregating Effects by Track

All senior high school students must take a core of English language, mathematics, integrated science and social studies, but they choose electives from one of the seven majors or tracks of study. These majors can be grouped into academically- or vocationally-oriented tracks of study. When students apply to senior high school, they apply not only to a particular school, but also to a particular major or track. Table A6, based on the comparison group in our study sample, shows the percentage of students admitted across the two types of majors. The split is about 40%-60% between academic and vocational majors, and there is no significant difference by gender.

There are two academically oriented majors, General Arts and General Science, and five vocationally oriented majors: Home Economics, Visual Arts, Agriculture, Technology, and Business. General Arts is by far the most popular track, and it includes elective subjects such as French and social science. General Science includes advanced mathematics, chemistry, biology and physics, but in our population of interest a very small share of students (less than 5%) gains admission in that track. While the split between academic and vocational majors does not vary by gender, the specific track within each major does – within vocational tracks, boys are more likely to be in Technology, Agriculture and Visual Arts, while girls are far more likely to be in Home Economics. Within academic tracks, boys are more likely to gain admission to General Science than girls. Switching majors upon enrolling is common, especially in rural areas where admission is less competitive. Table A6 shows that in the comparison group, among those who managed to enroll on their own, over a third of those admitted into a vocational track switched into an academic track (typically General Arts), and a quarter of those admitted in an academic track switched to a vocational track. This makes the pre-enrollment admission track an imperfect indicator of eventual track.

The results by track are shown in Table A7. The scholarship increased the senior high school completion rate from 47% to 79% (68% increase) for academic majors and from 45% to 70% (53% increase) for other majors. The difference in treatment effects between the two groups is not statistically significant (the p-value testing for the equality between coefficient estimates is 0.16).

Overall, the academic males who received the scholarship tend to look the same as the control group academic males. Across many outcomes, the treated students in the other three groups (academic females, vocational males and vocational females) tend to have significant differences from their control group counterparts. There are few outcomes where these pair-wise comparisons are significantly different from one another.

Appendix C: Using Scholarship Assignment as an Instrument for Education?

In this section, we discuss potential violations of the exclusion restriction and why we think they are minimal.

A first concern with using the scholarship assignment as an instrument is that the scholarship represented a wealth transfer to infra-marginal families who would have paid for senior high school in the absence of the scholarship. But it also reduced earnings by children induced to attend senior high school by the scholarship during the period of senior high school enrollment. We estimate that these effects roughly offset each other in our context.

To see this, note that for those who would have paid for senior high school themselves in the absence of a scholarship ("always takers"), the scholarship is akin to GHX[27] 2,328 cash transfer to the family of the student. As they make up about 50% of the scholarship winners (based on the control group, 58% would have enrolled anyway and 54.3% would have completed all four years absent the scholarship), this makes the wealth transfer GHX 1,164 on average for the treatment group as a whole.

In contrast, those who go to secondary school due to the scholarship ("compliers"), forego labor market earnings while in school and incur extra expenditure on school materials. Based on our estimates of foregone earnings while in senior high school and extra schooling expenditure over the lifetime of the scholarship (Table A2 Panel G), we calculate a total cost in 2017 GHX of 1,294. Reductions in unpaid household labor by students induced to attend senior high school by the

[27] All numbers reported in 2017 GHX.

scholarship presumably increase this amount, but we do not have the data to put a GHX value on this.

Overall, the positive and negative effects on household income are comparable in size and seem to offset each other (though obviously the gains and losses are experienced by different households – the always takers for the reduction in school fees and the compliers for the reduction in earnings-- and at different time periods).

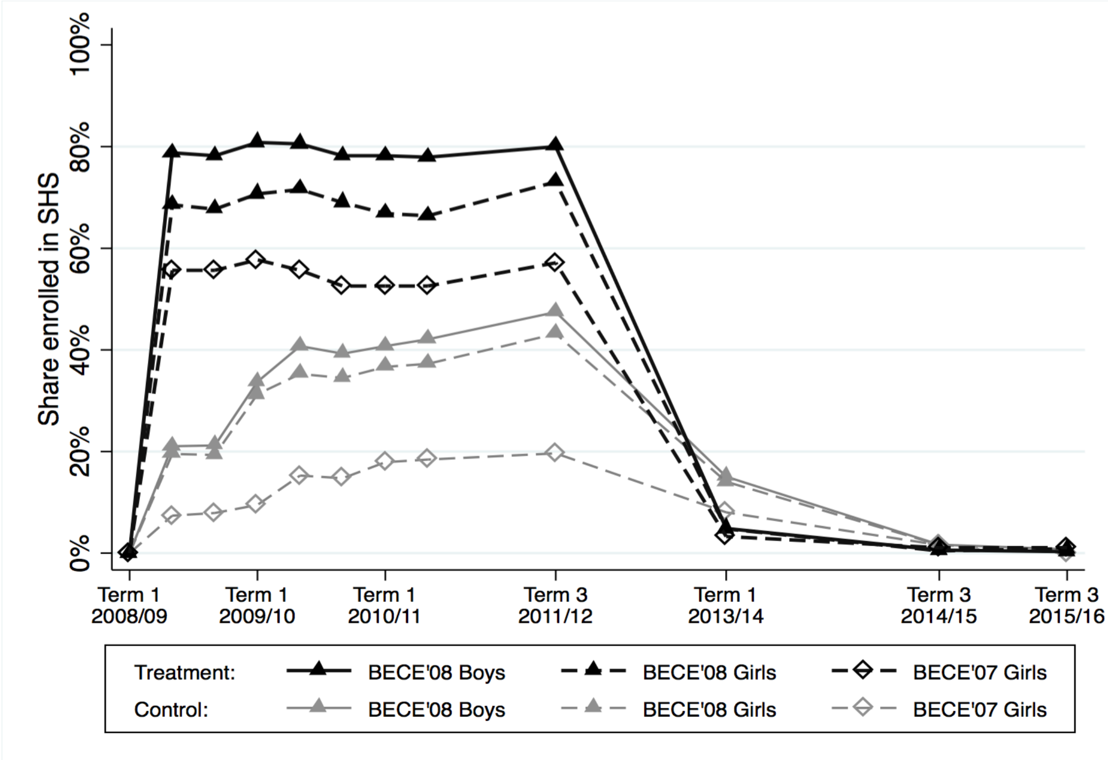
Table A2 Panel H presents evidence on the impacts of the scholarship on the educational attainment of siblings, and we find no such effect, consistent with the hypothesis that wealth effects on household investments due to the scholarship are small.

There could also be psychological effects of winning a lottery that are different from the effects of a scholarship per se. We collected data to check for this channel. As noted in Table A2 Panel B, we do not see large effects on risk or time preferences. We also see no evidence that the scholarship affected confidence levels (see Figure A3).

Overall the non-education impacts of the scholarship appear modest, suggesting that using the scholarship as an instrument for years of education may provide a reasonable approximation of the true effect.

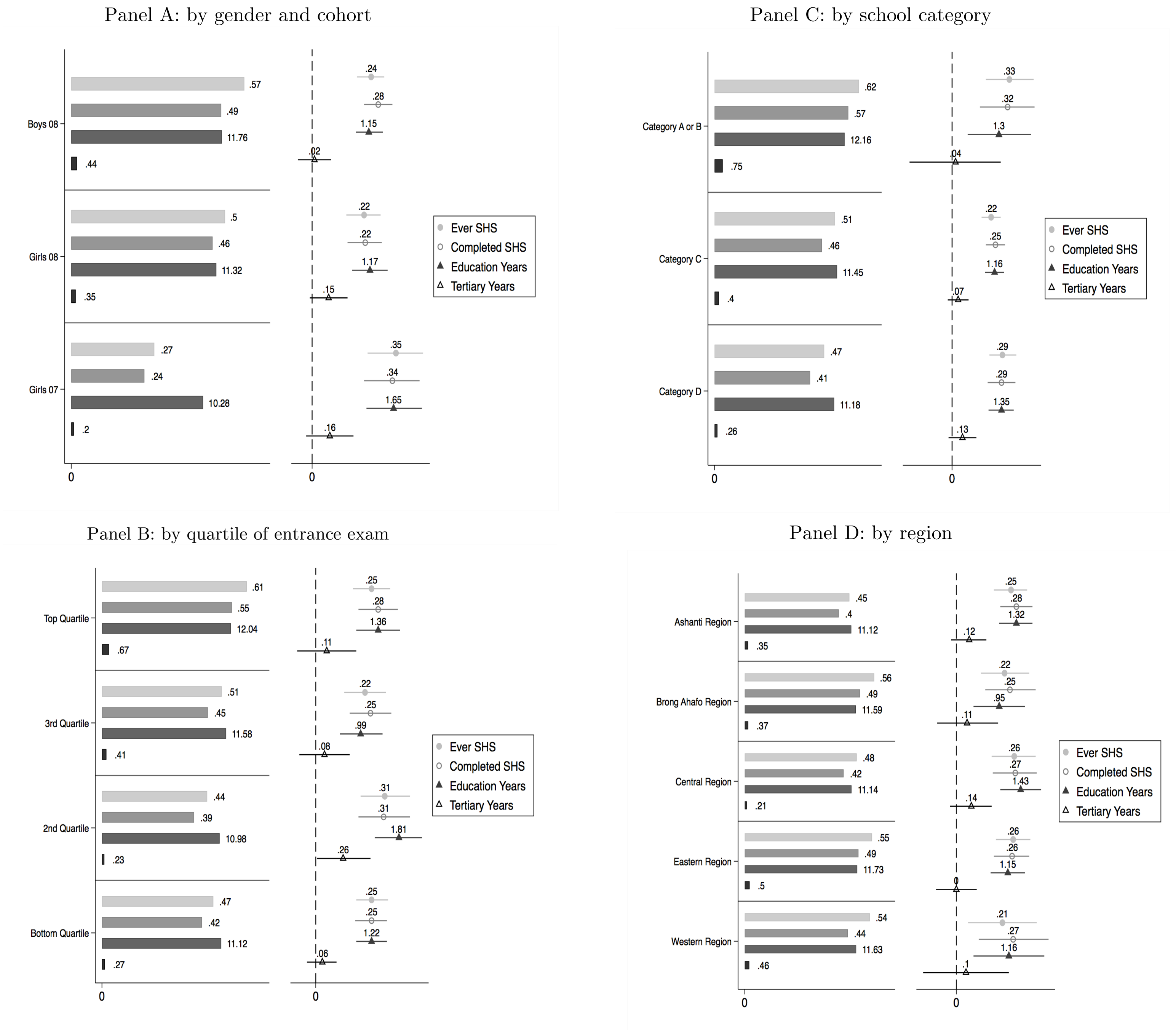
One other potential channel through which the exclusion restriction could be violated is if the scholarships affected later outcomes such as tertiary education, fertility, or labor market outcomes, not only by increasing the chance that marginal students ("compliers") would attend secondary school, but also by affecting effort in school, or other determinants of academic success, by infra-marginal students ("always takers"). Hypothetically, scholarships could have increased effort for these infra-marginal students by making them less likely to have been temporarily kicked out of school for failure to pay school fees, or to have experienced stress around this possibility, or by making them more certain that they would be able to afford to complete school. Of course, it is also possible that scholarships reduced effort among these students because they no longer had to fear withdrawal of financial support if they did not maintain high academic performance.

Figure 1: Impact of Scholarship on SHS Enrollment over time



Notes: Data from yearly phone surveys. The scholarships were awarded at the beginning of Term 2 of the 2008/2009 academic year. We split the sample into three types of students: boys who sat for the BECE in May 2008, girls who sat for the BECE in May 2008, and girls who sat for the BECE in May 2007. See text for details.

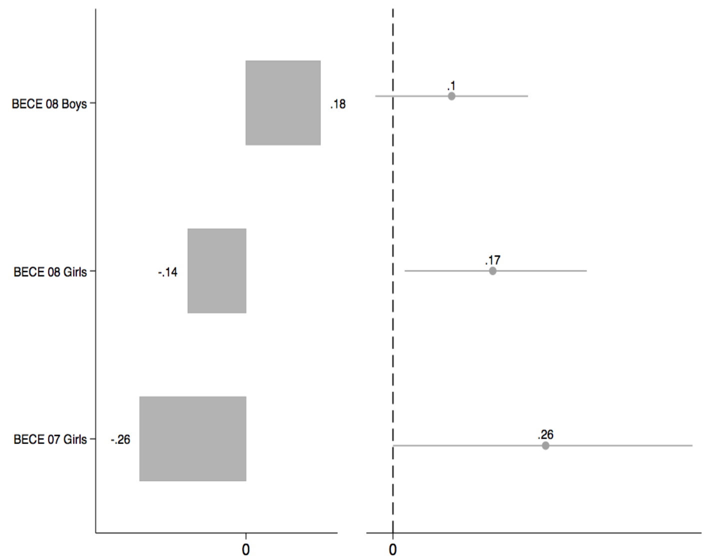
Figure 2: Effect of Scholarship on Educational Attainment as of 2019: subgroup analyses



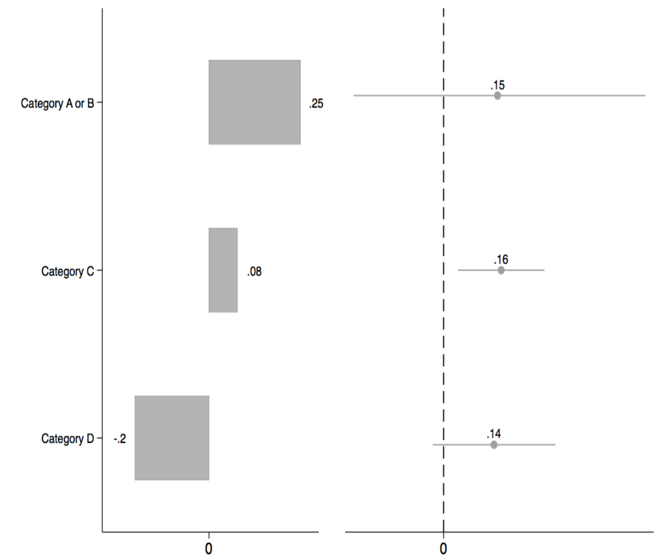
Data from 2019 callback survey.

Figure 3: Effect of Scholarship Treatment on Cognitive Skills after 5 years (2013): Subgroup analyses

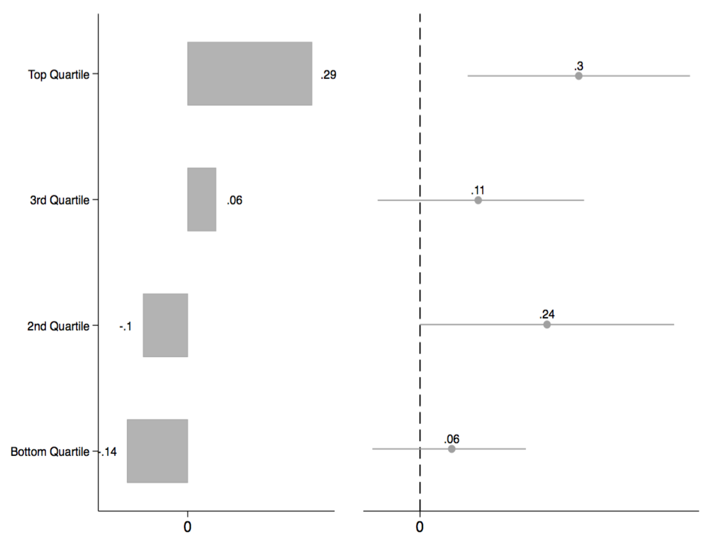
Panel A. by gender and cohort



Panel C. by category of the SHS of admission



Panel B. by quartile of entrance exam score



Panel D. by region

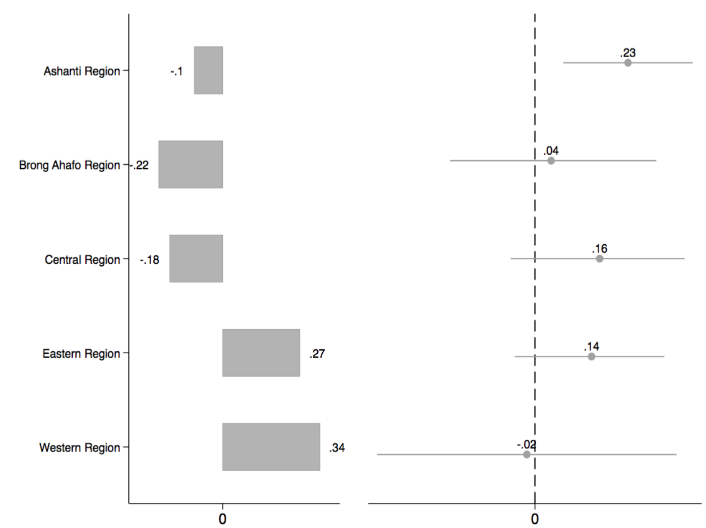


Figure 4A. Impact on onset of childbearing and yearly pregnancy hazard

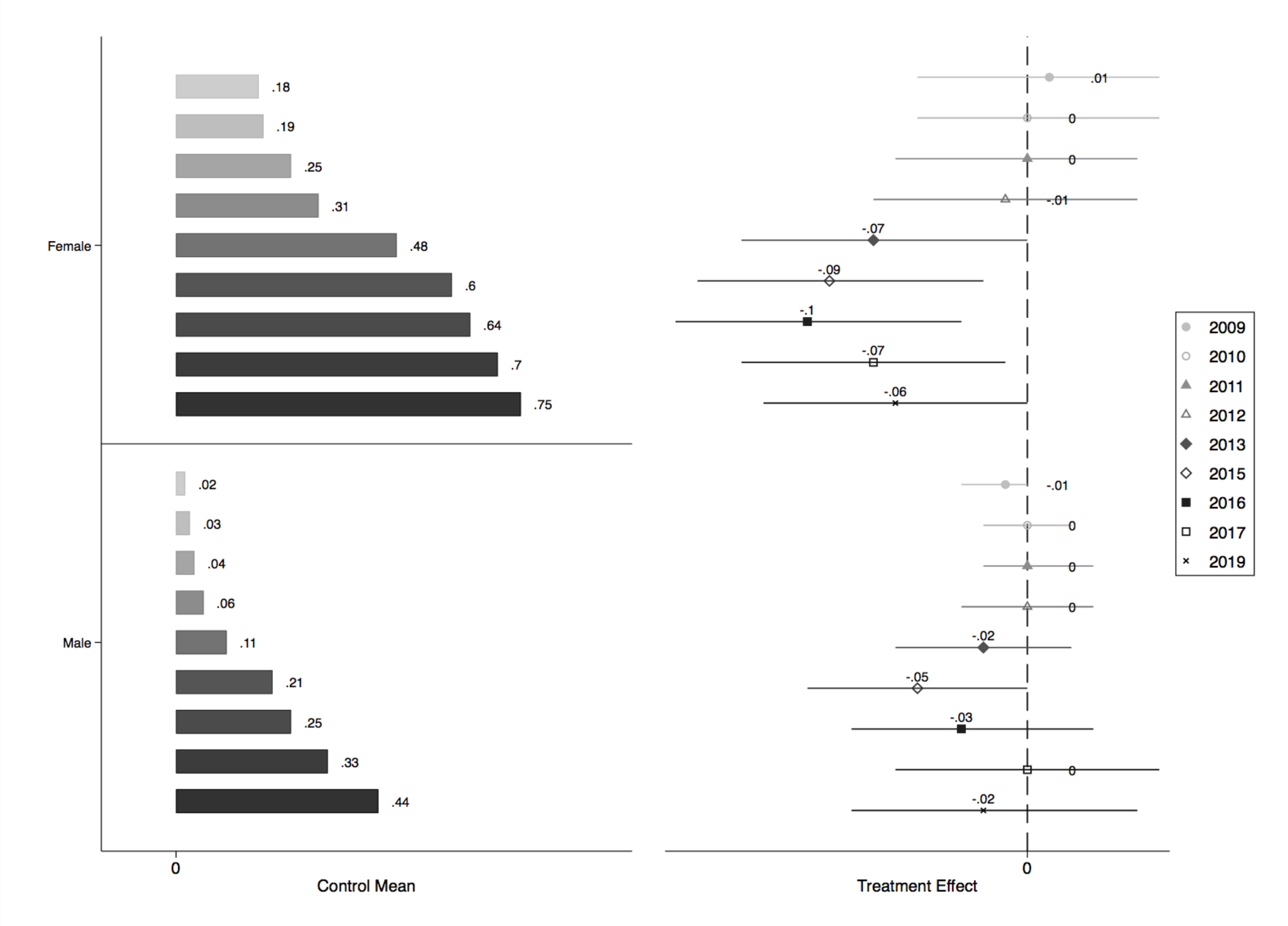
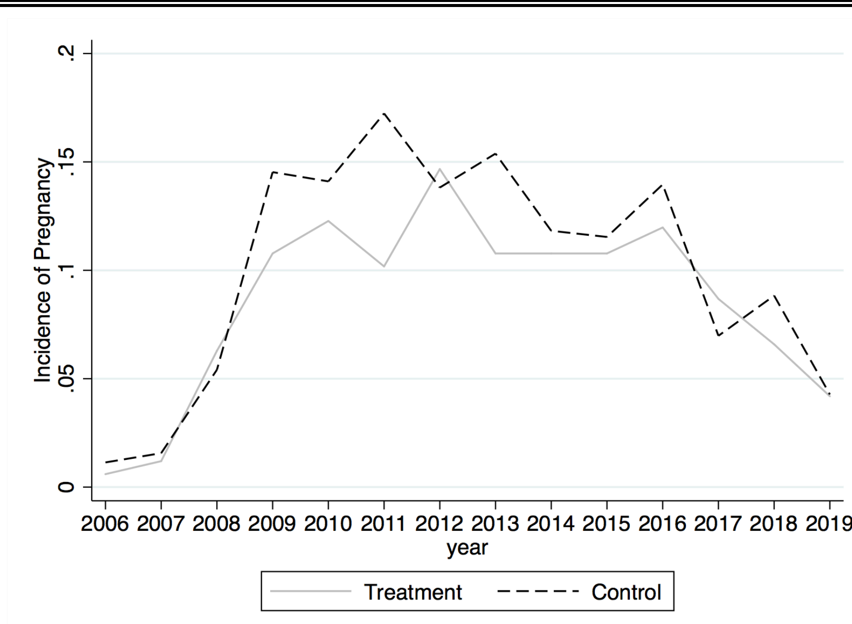


Figure 4B. Incidence of Pregnancy by Treatment status (Women Only)



Notes: Data from 2013 in-person follow-up, and phone surveys in 2009, 2010, 2011, 2012, 2015, 2016, 2017, and 2019. Ever pregnant means that the respondent or a partner of the respondent has ever been pregnant.

Figure 5. CDF of total earnings

Table 1: Sample Characteristics

	All	Female		Male	
	(1)	(2)	Obs	(3)	Obs
Age in 2008					
Treatment effect	-0.064	-0.048	1033	-0.084	1027
Standard error	(0.073)	(0.100)		(0.105)	
Comparison mean	17.369	17.314		17.426	
Completed BECE in 2007					
Treatment effect	0.005	0.020	1036	0.000	1028
Standard error	(0.016)	(0.030)		(0.002)	
Comparison mean	0.139	0.274		0.000	
BECE exam performance					
Treatment effect	0.002	-0.001	961	0.004	963
Standard error	(0.004)	(0.005)		(0.005)	
Comparison mean	0.623	0.618		0.628	
No male head in the household					
Treatment effect	0.009	-0.029	1031	0.047	1022
Standard error	(0.023)	(0.033)		(0.033)	
Comparison mean	0.425	0.455		0.395	
Number of HH members					
Treatment effect	-0.099	-0.148	1032	-0.054	1022
Standard error	(0.108)	(0.145)		(0.160)	
Comparison mean	5.659	5.617		5.703	
Highest education of HH head: primary education					
Treatment effect	-0.005	-0.014	1030	0.003	1019
Standard error	(0.009)	(0.013)		(0.013)	
Comparison mean	0.042	0.047		0.037	
Highest education of HH head: JHS					
Treatment effect	-0.009	-0.017	1030	-0.000	1019
Standard error	(0.022)	(0.032)		(0.032)	
Comparison mean	0.353	0.356		0.350	
Highest education of HH head: SHS					
Treatment effect	0.007	0.014	1030	0.001	1019
Standard error	(0.015)	(0.021)		(0.021)	
Comparison mean	0.111	0.106		0.116	
Highest education of HH head: TVI					
Treatment effect	-0.009	-0.013	1030	-0.005	1019
Standard error	(0.008)	(0.012)		(0.011)	
Comparison mean	0.036	0.040		0.031	
Highest education of HH head: tertiary					
Treatment effect	-0.009	-0.021	1030	0.002	1019
Standard error	(0.009)	(0.013)		(0.013)	
Comparison mean	0.050	0.057		0.041	
Perceived returns to SHS (%)					
Treatment effect	14.639	32.581	874	-1.955	908
Standard error	(28.106)	(39.897)		(39.771)	
Comparison mean	276.102	272.429		279.719	
Perceived returns to SHS education>100%					
Treatment effect	0.008	0.000	874	0.017	908
Standard error	(0.025)	(0.036)		(0.035)	
Comparison mean	0.463	0.478		0.448	
Ever had sex					
Treatment effect	-0.027	0.001	1034	-0.044	1027
Standard error	(0.022)	(0.033)		(0.025)*	
Comparison mean	0.328	0.454		0.199	
Self-reported financial situation (1-very comfortable->5-very poor)					
Treatment effect	0.044	0.020	1031	0.064	1015
Standard error	(0.032)	(0.044)		(0.045)	
Comparison mean	3.890	3.845		3.936	

Notes: Year of survey in parentheses. Col. 1 shows results for the full sample, Col. 2 for female males. Col. 4 shows the p-values for tests that the effects are identical between males and fem estimated treatment effects are in the first cell row; standard errors are in the second cell ro parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means

Table 2: Education Outcomes

	All	Female		Male		P-value
	(1)	(2)	Obs	(3)	Obs	Female=Male
Total years of education to date (2019)						
Treatment effect	1.238	1.297	968	1.153	956	.485
Standard error	(0.104)***	(0.155)***		(0.138)***		
Comparison mean	11.390	11.037		11.758		
Panel A. Secondary Education						
Ever enrolled in senior high school (2019)						
Treatment effect	0.250	0.251	1006	0.245	982	.881
Standard error	(0.021)***	(0.031)***		(0.029)***		
Comparison mean	0.502	0.440		0.566		
Completed SHS (2019)						
Treatment effect	0.267	0.253	1006	0.279	982	.553
Standard error	(0.022)***	(0.032)***		(0.030)***		
Comparison mean	0.445	0.402		0.491		
Panel B. Vocational Education						
Completed TVI (2019)						
Treatment effect	-0.024	-0.010	988	-0.037	967	.023***
Standard error	(0.006)***	(0.008)		(0.009)***		
Comparison mean	0.031	0.019		0.043		
Currently an apprentice (2019)						
Treatment effect	-0.011	-0.032	986	0.011	965	.084*
Standard error	(0.012)	(0.017)*		(0.018)		
Comparison mean	0.080	0.087		0.073		
Ever an apprentice (2017)						
Treatment effect	-0.144	-0.147	999	-0.145	979	.973
Standard error	(0.022)***	(0.031)***		(0.032)***		
Comparison mean	0.444	0.411		0.479		
Completed apprenticeship (2017)						
Treatment effect	-0.080	-0.070	996	-0.093	971	.519
Standard error	(0.018)***	(0.023)***		(0.027)***		
Comparison mean	0.222	0.184		0.262		
Panel C. Tertiary Education						
Currently enrolled in tertiary program (2019)						
Treatment effect	0.010	0.029	986	-0.008	965	.097*
Standard error	(0.011)	(0.015)*		(0.016)		
Comparison mean	0.049	0.035		0.065		
Ever enrolled in tertiary program (2019)						
Treatment effect	0.040	0.074	988	0.005	967	.055**
Standard error	(0.018)**	(0.025)***		(0.026)		
Comparison mean	0.152	0.122		0.183		
Completed tertiary (2019)						
Treatment effect	0.035	0.040	986	0.030	966	.733
Standard error	(0.015)**	(0.020)**		(0.022)		
Comparison mean	0.087	0.078		0.096		
Panel D. Schooling status as of last survey						
Enrolled in formal study/training (2019)						
Treatment effect	0.015	0.032	986	-0.002	965	.144
Standard error	(0.012)	(0.016)*		(0.017)		
Comparison mean	0.054	0.041		0.068		

Notes: Year of survey in parentheses. Col. 1 shows results for the full sample, Col. 2 for females, Col. 3 for males. Col. 4 shows the p-values for tests that the effects are identical between males and females. The estimated treatment effects are in the first cell row; standard errors are in the second cell row in parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means are in the third cell row. No control variables included.

Table 3: Skills and Technology Adoption

	Combined					
	All	Female	N	Male	N	P-value
	(1)	(2)		(3)		Female=Male
Panel A. Cognitive Skills						
Total standardized score (2013)						
Treatment effect	0.157	0.192	1002	0.112	981	.371
Standard error	(0.046)***	(0.069)***		(0.058)*		
Comparison mean	-0.000	-0.175		0.183		
Standardized score, Reading test (2013)						
Treatment effect	0.143	0.152	1002	0.129	981	.788
Standard error	(0.044)***	(0.067)**		(0.058)**		
Comparison mean	-0.000	-0.096		0.100		
Standardized score, Math test (2013)						
Treatment effect	0.125	0.172	1002	0.067	981	.246
Standard error	(0.046)***	(0.067)**		(0.060)		
Comparison mean	-0.000	-0.191		0.199		
Panel B. Knowledge						
National political knowledge standardized score (2013)						
Treatment effect	0.099	0.124	1001	0.059	980	.461
Standard error	(0.046)**	(0.063)**		(0.064)		
Comparison mean	0.000	-0.239		0.250		
International political knowledge standardized score (2013)						
Treatment effect	0.066	0.007	1001	0.098	980	.269
Standard error	(0.046)	(0.055)		(0.062)		
Comparison mean	0.000	-0.402		0.419		
Panel C. Connectedness						
Media engagement (radio, newspaper, TV, internet) (2013)	0.060	0.077	1001	0.035	980	.395
Treatment effect	(0.025)**	(0.032)**		(0.037)		
Standard error	-0.020	-0.165		0.131		
Comparison mean						
Knows how to use the internet (2013)						
Treatment effect	0.086	0.051	1001	0.101	982	.577
Standard error	(0.047)*	(0.058)		(0.067)		
Comparison mean	0.000	-0.333		0.346		
ICT/Social Media Adoption Index (2017)						
Treatment effect	0.084	0.161	997	-0.013	973	.029**
Standard error	(0.041)**	(0.059)***		(0.054)		
Comparison mean	-0.000	-0.229		0.243		
Used internet in the past month (2019)	0.059	0.074	985	0.037	965	.429
Treatment effect	(0.024)**	(0.033)**		(0.033)		
Standard error	0.493	0.402		0.590		
Comparison mean						
Panel D. Other Technology Adoption						
Owns a Bank Account (2013)	0.058	0.097	1002	0.015	982	.066**
Treatment effect	(0.023)**	(0.031)***		(0.033)		
Standard error	0.314	0.236		0.396		
Comparison mean						
Uses fertilizer (if involved in farming) (2017)	-0.024	0.020	337	-0.060	432	.290
Treatment effect	(0.037)	(0.057)		(0.050)		
Standard error	0.471	0.410		0.522		
Comparison mean						
Migrated to urban area (2019)						
Treatment effect	-0.008	-0.035	973	0.017	948	.201
Standard error	(0.021)	(0.028)		(0.030)		
Comparison mean	0.260	0.252		0.270		

Notes: See Table 2 notes. ICT adoption index (2017) is comprised of the following variables: knows how to use the internet, has internet access on mobile

Table 4: Fertility, Child Survival, Health Behavior, and Partners

	All	Female	N	Male	N	P-value
	(1)	(2)		(3)		Female=Male
Index of risky sexual behavior/STI exposure (safe --> risky) (2013)						
Treatment effect	-0.047	-0.014	1000	-0.074	980	.172
Standard error	(0.023)**	(0.030)		(0.033)**		
Comparison mean	0.001	0.095		-0.098		
Preventative health behavior (3 questions) (2013)						
Treatment effect	0.105	0.114	1002	0.100	982	.847
Standard error	(0.037)***	(0.052)**		(0.051)*		
Comparison mean	1.624	1.691		1.555		
Ever pregnant/had a pregnant partner (2013)						
Treatment effect	-0.047	-0.066	1009	-0.017	982	.209
Standard error	(0.021)**	(0.033)**		(0.020)		
Comparison mean	0.302	0.483		0.112		
Had unwanted first pregnancy (full sample) (2013)						
Treatment effect	-0.044	-0.066	985	-0.011	980	.136
Standard error	(0.019)**	(0.032)**		(0.017)		
Comparison mean	0.235	0.390		0.075		
Number of children ever had (2019)						
Treatment effect	-0.104	-0.147	986	-0.029	965	.245
Standard error	(0.053)*	(0.082)*		(0.060)		
Comparison mean	0.960	1.332		0.568		
Desired fertility: # of children by age 50 (2013)						
Treatment effect	-0.025	-0.040	999	-0.009	979	.750
Standard error	(0.048)	(0.064)		(0.072)		
Comparison mean	3.629	3.639		3.619		
Ever lived with partner(2016)						
Treatment effect	-0.091	-0.119	1026	-0.053	1011	.118
Standard error	(0.022)***	(0.033)***		(0.026)**		
Comparison mean	0.365	0.499		0.227		
Ever lived with partner (2019)						
Treatment effect	-0.036	-0.035	1017	-0.032	984	.941
Standard error	(0.022)*	(0.028)		(0.033)		
Comparison mean	0.727	0.802		0.646		
Most recent partner has tertiary education (2019)						
Treatment effect	0.019	0.072	575	-0.048	371	.007***
Standard error	(0.026)	(0.039)*		(0.022)**		
Comparison mean	0.148	0.195		0.072		
Still lives at parents' home (2019)						
Treatment effect	0.039	0.003	986	0.077	966	.097*
Standard error	(0.022)*	(0.033)		(0.031)**		
Comparison mean	0.300	0.355		0.242		
Used prenatal care for last pregnancy (2019)						
Treatment effect	0.009	0.011	642	0.007	328	.829
Standard error	(0.007)	(0.005)**		(0.019)		
Comparison mean	0.982	0.989		0.967		
Any child deceased before age 3 (2019)						
Treatment effect	-0.025	-0.036	556	0.001	233	.418
Standard error	(0.021)	(0.025)		(0.038)		
Comparison mean	0.092	0.099		0.076		

Notes: See Table 2 notes. Index of risky sexual behavior and STI exposure (2013) is comprised of the following variables: have you ever had sex, age when first had sex, number of sexual partners in past 6 months, number of lifetime sexual partners, were you ever in a relationship with someone more than 20 years older, were you ever in a relationship for gifts or money, have you ever had sex with a commercial sex worker, did you use contraception the last time you had sex, have you ever used contraception when having sex, do you ever do anything to protect yourself fro getting infected with HIV/AIDs, have you had a sexually transmitted infection in the past 12 months, has partner ever told you that they had a sexually transmitted infection, did you change how often you had sex after learning that partner was infected with STI.

Table 5: Sector of work

Panel A. Sector of Work	All (1)	Female (2)	N	Male (3)	N	P-value Female=Male
Public sector employee (2017)						
Treatment effect	0.032	0.041	996	0.023	972	.384
Standard error	(0.010)***	(0.014)***		(0.014)		
Comparison mean	0.026	0.021		0.031		
Public sector employee (2019)						
Treatment effect	0.017	0.038	986	-0.004	966	.091*
Standard error	(0.013)	(0.017)**		(0.018)		
Comparison mean	0.065	0.048		0.084		
Waiting for public service posting (2019)						
Treatment effect	0.019	0.012	986	0.026	966	.426
Standard error	(0.009)**	(0.012)		(0.014)*		
Comparison mean	0.025	0.026		0.024		
Has a wage contract with employer (2017)						
Treatment effect	0.033	0.025	996	0.040	972	.565
Standard error	(0.013)**	(0.018)		(0.019)**		
Comparison mean	0.061	0.058		0.064		
Has a wage contract with employer (2019)						
Treatment effect	0.039	0.041	986	0.036	965	.856
Standard error	(0.015)***	(0.019)**		(0.023)		
Comparison mean	0.084	0.063		0.106		
Job with benefits (2017)						
Treatment effect	0.045	0.042	996	0.046	972	.894
Standard error	(0.015)***	(0.020)**		(0.023)**		
Comparison mean	0.084	0.066		0.103		
Job with benefits (2019)						
Treatment effect	0.030	0.020	986	0.037	965	.571
Standard error	(0.015)*	(0.019)		(0.024)		
Comparison mean	0.099	0.075		0.125		
Self-employed (2017)						
Treatment effect	-0.050	-0.077	996	-0.019	972	.145
Standard error	(0.020)**	(0.030)***		(0.027)		
Comparison mean	0.255	0.305		0.202		
Self-employed (2019)						
Treatment effect	-0.029	-0.014	986	-0.039	966	.535
Standard error	(0.020)	(0.031)		(0.026)		
Comparison mean	0.245	0.287		0.201		
Panel B. Industry						
Transport or Construction (2017)						
Treatment effect	-0.014	0.007	997	-0.046	972	.048**
Standard error	(0.014)	(0.006)		(0.026)*		
Comparison mean	0.106	0.001		0.218		
Transport or Construction (2019)						
Treatment effect	-0.013	0.002	986	-0.037	966	.143
Standard error	(0.014)	(0.005)		(0.027)		
Comparison mean	0.109	0.003		0.221		
Services (excluding pubic service) (2017)						
Treatment effect	0.007	-0.038	997	0.053	972	.018**
Standard error	(0.019)	(0.027)		(0.028)*		
Comparison mean	0.203	0.227		0.178		
Services (excluding pubic service) (2019)						
Treatment effect	-0.006	-0.055	986	0.045	966	.012**
Standard error	(0.020)	(0.028)*		(0.028)		
Comparison mean	0.227	0.260		0.193		
Petty trade (2017)						
Treatment effect	-0.040	-0.057	997	-0.013	972	.128
Standard error	(0.015)***	(0.026)**		(0.011)		
Comparison mean	0.131	0.219		0.038		
Petty trade (2019)						
Treatment effect	0.003	0.008	986	0.004	966	.880
Standard error	(0.015)	(0.026)		(0.013)		
Comparison mean	0.108	0.176		0.036		
Franchise/Large trade (2017)						
Treatment effect	0.009	0.020	997	-0.003	972	.258
Standard error	(0.010)	(0.014)		(0.015)		
Comparison mean	0.041	0.031		0.052		
Franchise/Large trade (2019)						
Treatment effect	0.015	0.033	986	-0.004	966	.035**
Standard error	(0.009)	(0.013)***		(0.013)		
Comparison mean	0.027	0.014		0.041		

Notes: See Table 2 notes

Table 6: Labor supply and Earnings

	All	Female	N	Male	N	P-value
	(1)	(2)		(3)		Female=Male
Panel A. Labor Supply						
Worked for pay in past 6 months (2017)						
Treatment effect	0.031	0.021	997	0.030	973	.835
Standard error	(0.021)	(0.033)		(0.023)		
Comparison mean	0.733	0.629		0.844		
Worked for pay in past 6 months (2019)						
Treatment effect	0.011	0.032	986	-0.020	966	.207
Standard error	(0.021)	(0.033)		(0.024)		
Comparison mean	0.730	0.602		0.864		
Total hours worked last month (if worked at least 10 hours) (2017)						
Treatment effect	-1.778	-4.094	442	-0.082	658	.740
Standard error	(5.988)	(9.258)		(7.830)		
Comparison mean	148.540	151.909		146.172		
Total hours worked last month (if worked at least 10 hours) (2019)						
Treatment effect	-8.647	6.029	467	-18.846	668	.020**
Standard error	(5.371)	(8.082)		(7.116)***		
Comparison mean	151.950	141.032		159.530		
Panel B. Earnings						
Total earnings in past 6 months (2017)						
Treatment effect	83.229	81.617	969	53.510	932	.819
Standard error	(62.870)	(78.812)		(94.282)		
Comparison mean	944.657	647.492		1264.158		
Total earnings in past 6 months (2019)						
Treatment effect	37.123	31.022	972	-6.278	943	.837
Standard error	(93.450)	(108.289)		(145.665)		
Comparison mean	1456.217	951.456		1993.862		
Log earnings in past 6 months (2017)						
Treatment effect	0.105	0.142	577	0.048	767	.471
Standard error	(0.064)	(0.103)		(0.079)		
Comparison mean	6.736	6.437		6.973		
Log earnings in past 6 months (2019)						
Treatment effect	-0.048	0.003	573	-0.082	799	.538
Standard error	(0.068)	(0.108)		(0.084)		
Comparison mean	7.178	6.857		7.408		
Coefficient of variation of weekly earnings (GHX) (2017)						
Treatment effect	-2.420	0.968	422	-4.921	585	.247
Standard error	(2.443)	(4.100)		(3.034)		
Comparison mean	26.704	24.374		28.493		
Coefficient of variation of weekly earnings (GHX) (2019)						
Treatment effect	-4.411	-7.250	438	-2.489	628	.415
Standard error	(2.870)	(4.474)		(3.748)		
Comparison mean	28.412	27.668		28.940		
Earnings per hour if worked >20 hrs in past month and not self-employed (2017)						
Treatment effect	0.082	0.357	230	-0.067	471	.250
Standard error	(0.186)	(0.273)		(0.240)		
Comparison mean	2.583	1.797		2.972		
Earnings per hour if worked >20 hrs in past month and not self-employed (2019)						
Treatment effect	-0.240	-0.612	238	0.016	506	.271
Standard error	(0.270)	(0.439)		(0.348)		
Comparison mean	3.927	3.421		4.149		
Would not be able to deal with 200 GHX emergency (2017)						
Treatment effect	0.013	0.005	994	0.024	965	.595
Standard error	(0.018)	(0.027)		(0.023)		
Comparison mean	0.153	0.183		0.121		
Would not be able to cope with a 200 GHX emergency (2019)						
Treatment effect	-0.027	-0.043	986	-0.009	965	.319
Standard error	(0.017)	(0.024)*		(0.024)		
Comparison mean	0.161	0.176		0.146		

Notes: See Table 2 notes

Table 7: Earnings Bounds for females not induced by the program to still be in tertiary

	2017		2019	
	(1)	N	(2)	N
Total earnings last 6 months (GHX) (2017)				
Lower Bound (=Table 6)				
Treatment effect	81.617	969	31.022	972
Standard error	(78.812)		(108.289)	
Comparison mean	647.492		951.456	
Upper Bound				
Treatment effect	266.772	969	276.384	972
Standard error	(77.311)***		(115.107)**	
Comparison mean	647.492		951.456	
Log Total Earnings in last 6 months if any				
Lower Bound (=Table 6)				
Treatment effect	0.142	577	0.003	573
Standard error	(0.103)		(0.108)	
Comparison mean	6.437		6.857	
Upper Bound				
Treatment effect	0.280	577	0.021	573
Standard error	(0.104)***		(0.110)	
Comparison mean	6.437		6.857	
Earnings per hour if worked>20h and not self employed (2017)				
Lower Bound (=Table 6)				
Treatment effect	0.357	230	-0.612	238
Standard error	(0.273)		(0.439)	
Comparison mean	1.797		3.421	
Upper Bound				
Treatment effect	0.651	230	-0.211	238
Standard error	(0.221)***		(0.330)	
Comparison mean	1.797		3.421	

Notes: Column 1 shows bounds for 2017 and column 2 shows bounds for 2019. We only compute bounds for females since there is no differential tertiary enrollment for males. Bounds are calculated in the following way: Let X be the treatment effect on currently attenting tertiary school. For upper bounds, top X% of control earners removed. All respondents currently enrolled in tertiary removed for bounds calculations.

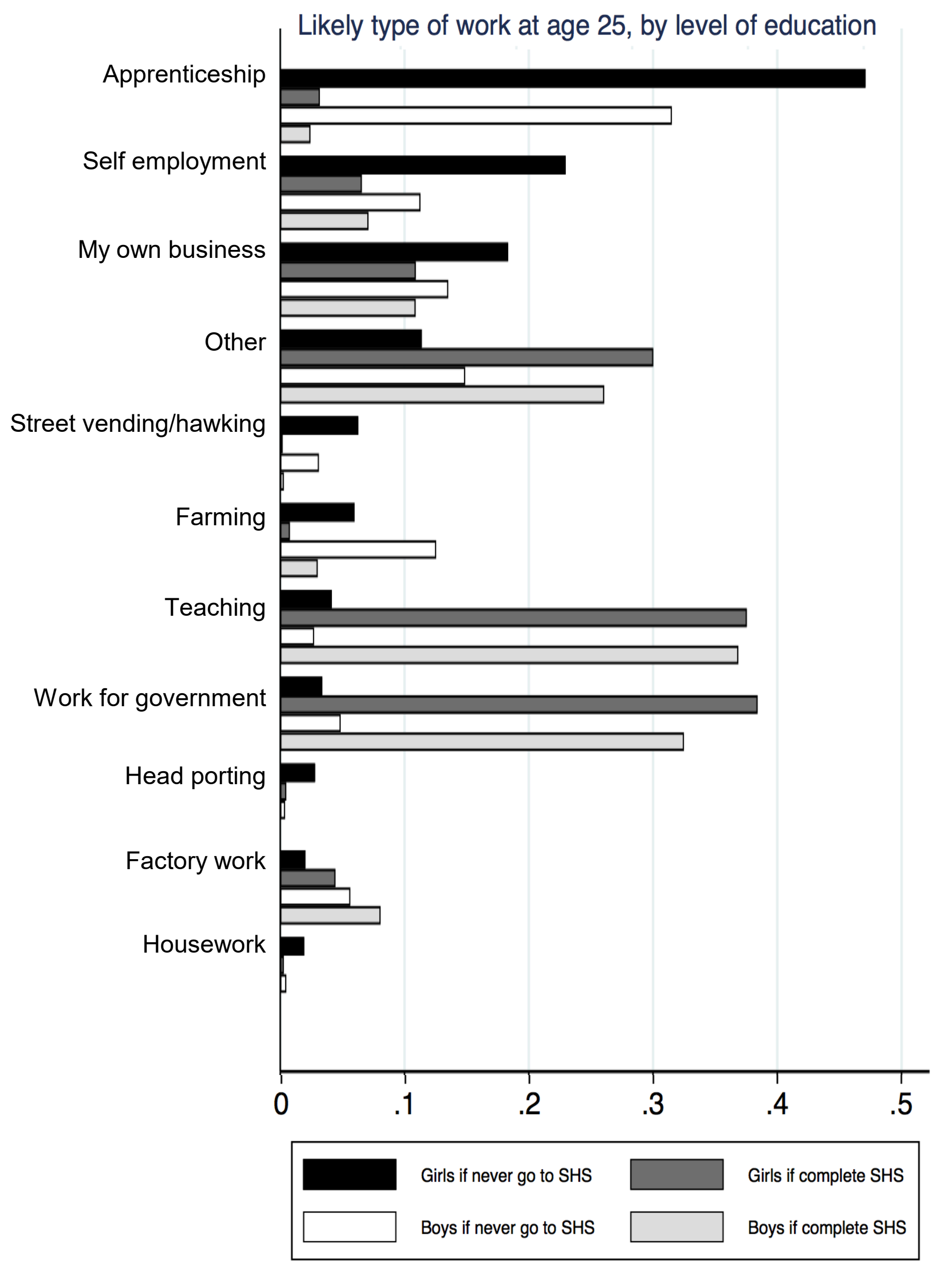
Table 8: Can IV estimates be recovered with ML?

	OLS without any controls	OLS with controls	DoubleML	Weighted DoubleML (LATE)	IV
Panel A: Female					
Total standardized score (2013)	0.249	0.239	0.21	0.214	0.139
	(0.019)*	(0.019)*	(0.02)*	(0.021)*	(0.051)*
Number of children ever (2017)	-0.207	-0.206	-0.162	-0.17	-0.153
	(0.016)*	(0.016)*	(0.016)*	(0.017)*	(0.053)*
Preventive health index (2013)	0.007	-0.003	0.005	0.017	0.1
	(0.017)	(0.017)	(0.017)	(0.019)	(0.043)*
Ever enrolled in tertiary (2019)	0.095	0.094	0.093	0.087	0.057
	(0.005)*	(0.005)*	(0.006)*	(0.007)*	(0.015)*
Work sector index (2019)	0.033	0.032	0.035	0.034	0.028
	(0.004)*	(0.004)*	(0.005)*	(0.005)*	(0.01)*
Hours worked last month (if $>$ 10 hours) (2017)	7.373	6.286	6.334	6.113	-1.178
	(2.642)*	(2.639)*	(2.912)*	(3.152)	(6.469)
Total earnings in the past 6 months (2019)	138.26	140.108	136.978	156.749	10.684
	(32.033)*	(33.236)*	(35.114)*	(38.172)*	(89.468)
Wage earnings per hour (if worked $>$ 20 hours) (2019)	0.131	0.125	0.12	-0.023	-0.495
	(0.130)	(0.128)	(0.138)	(0.160)	(0.411)
Panel B: Male					
Total standardized score (2013)	0.156	0.147	0.123	0.128	0.088
	(0.02)*	(0.019)*	(0.019)*	(0.02)*	(0.053)
Number of children ever (2017)	-0.085	-0.085	-0.074	-0.074	-0.022
	(0.014)*	(0.014)*	(0.014)*	(0.015)*	(0.041)
Preventive health index (2013)	0.024	0.023	0.024	0.028	0.093
	(0.017)	(0.017)	(0.018)	(0.018)	(0.050)
Ever enrolled in tertiary (2019)	0.106	0.105	0.104	0.105	0.003
	(0.005)*	(0.005)*	(0.005)*	(0.005)*	(0.023)
Work sector index (2019)	0.027	0.026	0.028	0.028	0.024
	(0.004)*	(0.004)*	(0.004)*	(0.005)*	(0.014)
Hours worked last month (if $>$ 10 hours) (2017)	0.156	0.504	-0.647	-0.333	0.065
	(2.148)	(2.193)	(2.237)	(2.385)	(7.016)
Total earnings in the past 6 months (2019)	20.604	11.69	29.192	34.851	-36.115
	(34.643)	(34.498)	(36.423)	(38.631)	(126.790)
Wage earnings per hour (if worked $>$ 20 hours) (2019)	0.036	0.023	0.041	0.027	-0.061
	(0.071)	(0.074)	(0.075)	(0.084)	(0.329)

Notes: See text section 8 for details. Col. 1 shows results from an OLS regression (control group only) with years of education as the dependent variable and without any controls. Col. 2 shows results from an OLS regression (control group only) with years of education as the dependent variables and controlling for region fixed effects, JHS finishing exam score (BECE), missing JHS finishing exam scores, and baseline variables. Col. 3 shows results using the Double Machine Learning (DML) procedure. Col. 4 shows results using the DML (LATE) procedure. Col. 5 shows results from IV regressions using years of education as an instrument for treatment. For all regressions, * indicates significance at 5%. In 2013, 1,280 observations for OLS and 1,907 observations for IV. In 2017, 1,266 observations for OLS and 1,891 for IV. Refer to Table A3 for the components of the indices.

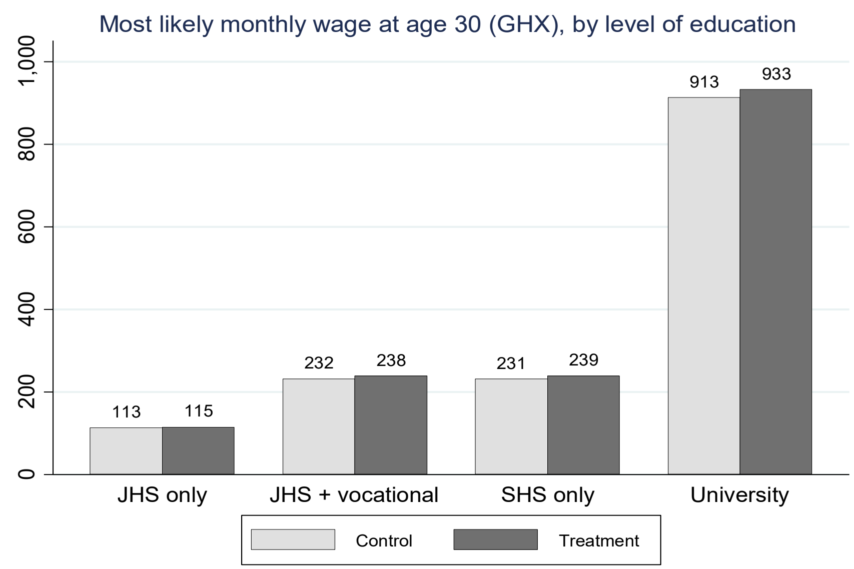
Figure A1. Expectations

Panel A. Participant's beliefs about education and work at 2008 baseline



Note: Data from 2008 in-person baseline survey of participants

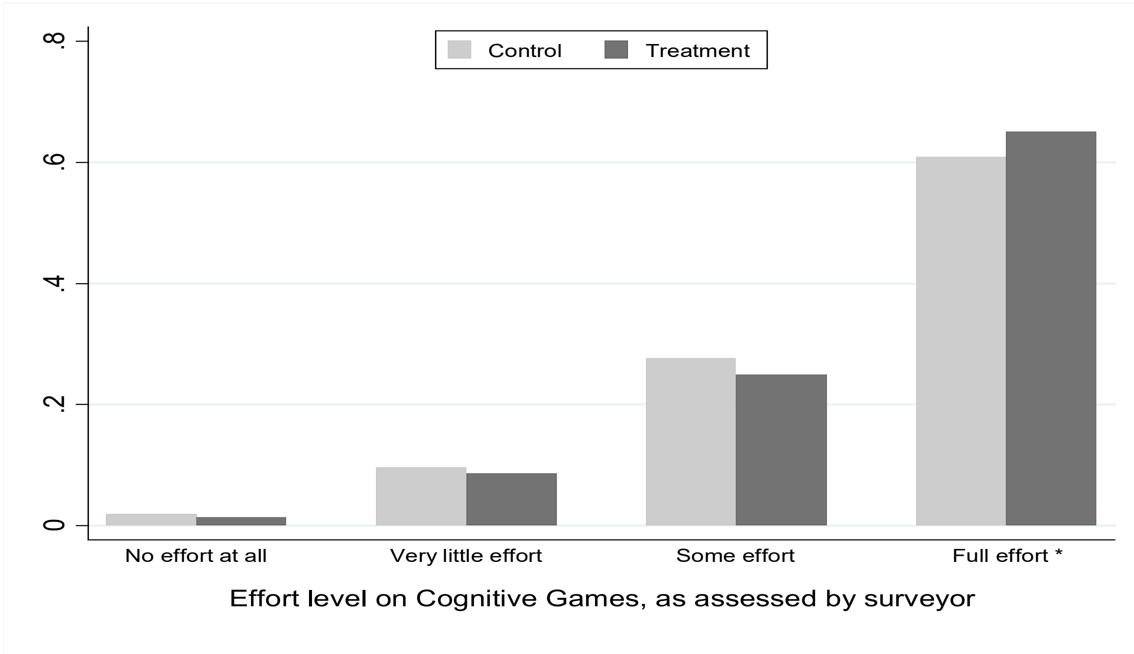
Panel B. Guardian beliefs about returns to education at 2013 follow-up



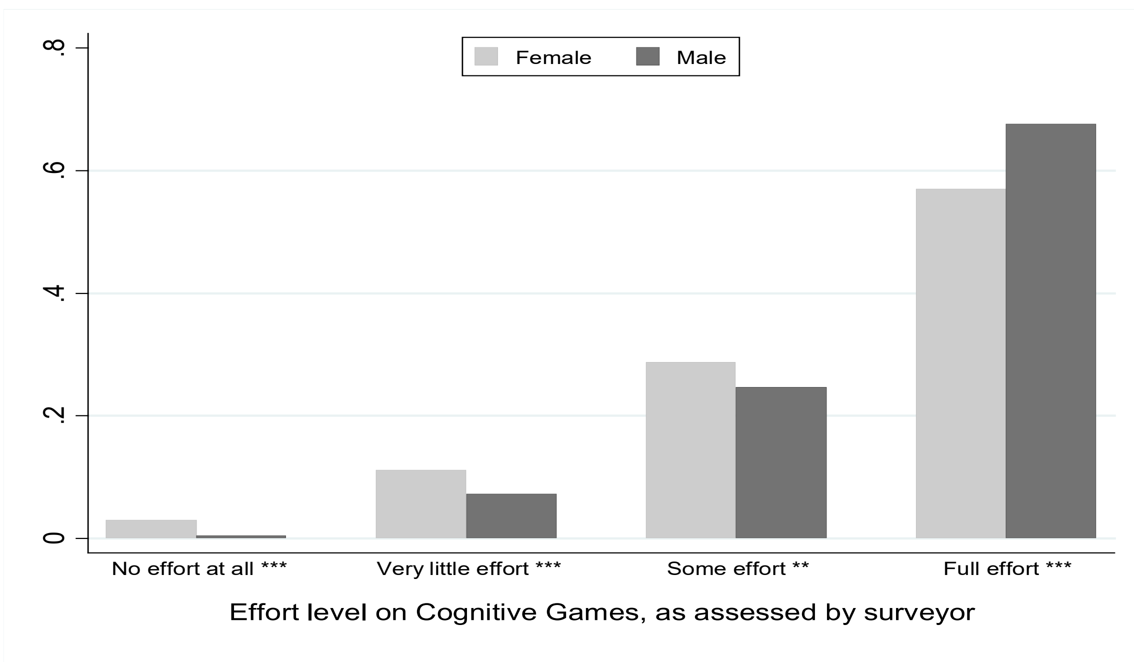
Note: Data from 2013 in-person follow-up survey with guardians of youths in the primary study sample.

Figure A2. Effort Level on Cognitive Test "Games" during 2013 follow-up survey

Panel A. By Scholarhip (Treatment) Status

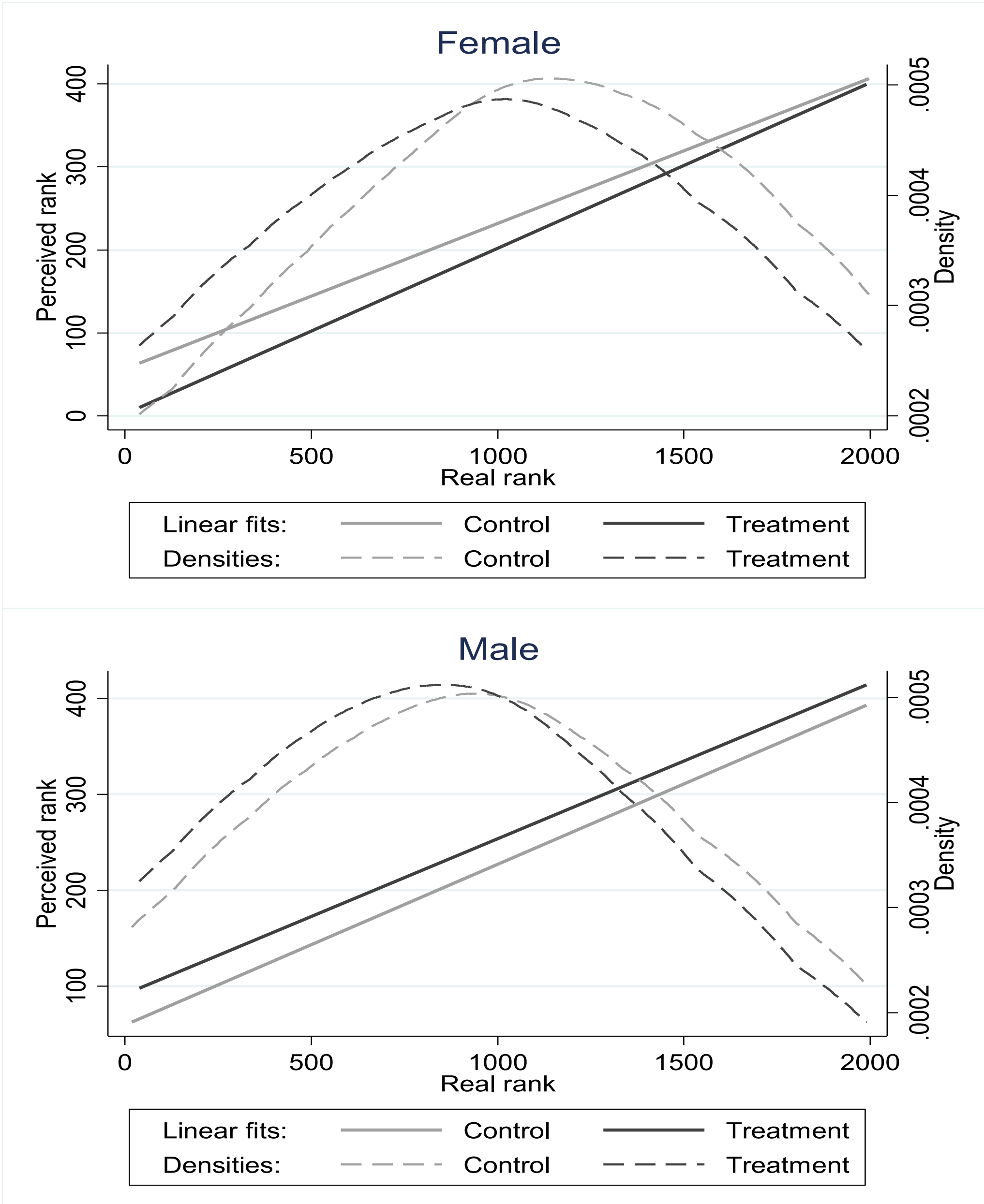


Panel B. By Gender



Note: Data from 2013 in-person follow-up survey.

Figure A3. Effects of Scholarship on accuracy of beliefs about relative performance



Notes: "Real rank" is the rank on the math and reading comprehension test administered during the 2013 follow-up survey. "Perceived rank" is the rank that the respondent reported when asked, immediately after the test: "We are administering this survey to around 2,000 youths your age (1,000 boys and 1,000 girls). All of those we are interviewing completed JHS around the same time as you, in 2007 or 2008. Overall, how do you think your performance on the games will compare to that of the others? Try to guess your rank between 1 and 2,000, with 1 being the person with the highest/top score and 2000 being the person with the lowest score."

Table A1: Attrition

	All	Female		Male		P-value
	(1)	(2)	Obs	(3)	Obs	Female=Male
Surveyed (2013)						
Treatment effect	-0.005	0.001	1036	-0.010	1028	.557
Standard error	(0.009)	(0.012)		(0.014)		
Comparison mean	0.963	0.967		0.959		
Surveyed (2016)						
Treatment effect	0.009	0.007	1036	0.012	1028	.772
Standard error	(0.008)	(0.011)		(0.012)		
Comparison mean	0.964	0.970		0.957		
Surveyed (2017)						
Treatment effect	0.001	-0.013	1036	0.017	1028	.127
Standard error	(0.010)	(0.013)		(0.014)		
Comparison mean	0.954	0.967		0.941		
Surveyed (2019)						
Treatment effect	0.020	0.014	1036	0.026	1028	.557
Standard error	(0.010)**	(0.013)		(0.015)*		
Comparison mean	0.939	0.947		0.931		
Refused (2017)						
Treatment effect	-0.005	-0.006	1036	-0.005	1028	.891
Standard error	(0.004)	(0.006)		(0.006)		
Comparison mean	0.011	0.011		0.010		
Refused (2019)						
Treatment effect	-0.017	-0.018	1036	-0.016	1028	.886
Standard error	(0.005)***	(0.008)**		(0.007)**		
Comparison mean	0.025	0.027		0.022		

Notes: Year of survey in parentheses. Col. 1 shows results for the full sample, Col. 2 for females, Col. 3 for males. Col. 4 shows the p-values for tests that the effects are identical between males and females. The estimated treatment effects are in the first cell row; standard errors are in the second cell row in parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means are in the third cell row. No control variables included.

Table A2: Other outcomes

	All	Female		Male		P-value
	(1)	(2)	Obs	(3)	Obs	Female=Male
Panel A. Tertiary Plans						
Sat for WASSCE exam (2019)						
Treatment effect	0.256	0.255	1005	0.252	981	.944
Standard error	(0.022)***	(0.032)***		(0.030)***		
Comparison mean	0.474	0.414		0.538		
Plans to apply to tertiary (2017)						
Treatment effect	0.150	0.150	997	0.143	973	.879
Standard error	(0.023)***	(0.033)***		(0.032)***		
Comparison mean	0.489	0.427		0.555		
Plans to apply as Mature Applicant (2017)						
Treatment effect	0.098	0.121	997	0.072	973	.293
Standard error	(0.024)***	(0.033)***		(0.034)**		
Comparison mean	0.384	0.337		0.434		
Applied as Mature Applicant (2019)						
Treatment effect	0.012	0.013	986	0.011	966	.883
Standard error	(0.008)	(0.011)		(0.011)		
Comparison mean	0.020	0.018		0.022		
Plans to apply to tertiary (2019)						
Treatment effect	0.149	0.179	986	0.114	966	.169
Standard error	(0.024)***	(0.033)***		(0.033)***		
Comparison mean	0.366	0.286		0.450		
Panel B. Cognitive Skills, Preferences (2013)						
Memory for digit span (forward) (2013)						
Treatment effect	0.009	-0.027	1002	0.033	981	.801
Standard error	(0.120)	(0.170)		(0.169)		
Comparison mean	7.544	7.381		7.714		
Memory for digit span (backward) (2013)						
Treatment effect	0.109	0.048	1002	0.159	981	.518
Standard error	(0.086)	(0.118)		(0.125)		
Comparison mean	4.541	4.374		4.714		
Raven's progressive matrices (2013)						
Treatment effect	-0.001	-0.022	1001	-0.004	980	.939
Standard error	(0.119)	(0.168)		(0.165)		
Comparison mean	6.954	6.558		7.368		
Trust in general (2013)						
Treatment effect	0.083	0.147	1001	0.017	980	.060**
Standard error	(0.035)**	(0.048)***		(0.050)		
Comparison mean	0.000	-0.044		0.047		
Amount willing to invest in high payoff but risky business						
Treatment effect	1.011	0.352	1001	1.651	980	.634
Standard error	(1.365)	(1.970)		(1.892)		
Comparison mean	51.077	51.136		51.015		
Amount needed in two days to forego 40 GHX today						
Treatment effect	-0.993	-2.112	1001	-0.008	980	.859
Standard error	(5.917)	(8.126)		(8.620)		
Comparison mean	100.783	99.727		101.885		

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Time consistent						
Treatment effect	0.014	0.009	1001	0.019	980	.818
Standard error	(0.024)	(0.033)		(0.033)		
Comparison mean	0.409	0.400		0.418		
Present-bias						
Treatment effect	0.001	0.002	1001	0.001	980	.964
Standard error	(0.021)	(0.030)		(0.029)		
Comparison mean	0.258	0.270		0.245		
Extremely impatient in both present and future						
Treatment effect	-0.002	-0.008	1002	0.003	982	.669
Standard error	(0.013)	(0.018)		(0.019)		
Comparison mean	0.087	0.085		0.089		
Panel C. Civic participation						
Has voting card (2013)						
Treatment effect	0.015	0.017	1000	0.013	980	.833
Standard error	(0.008)*	(0.011)		(0.012)		
Comparison mean	0.961	0.962		0.960		
Voted in the 2012 National Elections (2013)						
Treatment effect	-0.025	-0.019	999	-0.032	978	.734
Standard error	(0.018)	(0.027)		(0.025)		
Comparison mean	0.837	0.817		0.858		
Voted in last District Assembly election (2013)						
Treatment effect	-0.006	-0.031	999	0.018	980	.247
Standard error	(0.021)	(0.029)		(0.031)		
Comparison mean	0.281	0.269		0.294		
Voted in 2016 national election (2017)						
Treatment effect	-0.016	-0.023	995	-0.012	970	.786
Standard error	(0.021)	(0.030)		(0.028)		
Comparison mean	0.759	0.739		0.780		
Voted in last District Assembly election (2017)						
Treatment effect	-0.019	-0.056	995	0.016	970	.129
Standard error	(0.024)	(0.033)*		(0.033)		
Comparison mean	0.463	0.461		0.465		
Panel D. Reservation Wage						
Lowest daily wage willing to work for (GHX)(2013)						
Treatment effect	-0.498	0.811	995	-1.890	981	.013**
Standard error	(0.542)	(0.733)		(0.800)**		
Comparison mean	9.949	8.012		11.959		
Willing to move for wage employment (2013)						
Treatment effect	0.009	0.003	1000	0.014	979	.738
Standard error	(0.016)	(0.024)		(0.021)		
Comparison mean	0.870	0.854		0.888		
Willing to do labor intensive work (2013)						
Treatment effect	-0.001	0.007	1000	-0.014	979	.632
Standard error	(0.023)	(0.033)		(0.030)		
Comparison mean	0.640	0.555		0.729		

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Panel E. Mental health and satisfaction						
Mental health index(1-depressed-->5-positive)(average over 7 questions)(2013)						
Treatment effect	-0.002	-0.013	1001	0.007	980	.828
Standard error	(0.048)	(0.065)		(0.069)		
Comparison mean	-0.000	-0.037		0.038		
Satisfaction Index(1-very unsatisfied-->5-very satisfied)(2013)						
Treatment effect	-0.001	0.094	1001	-0.095	980	.012**
Standard error	(0.038)	(0.052)*		(0.054)*		
Comparison mean	3.318	3.310		3.327		
If employed: satisfaction with job(1-very unsatisfied-->5-very satisfied)(2017)						
Treatment effect	-0.196	-0.087	542	-0.266	676	.290
Standard error	(0.084)**	(0.127)		(0.113)**		
Comparison mean	3.773	3.819		3.734		
Panel F. Job Search						
Confident can get a better job(1-not sure possible --> 5-very confident)(2017)						
Treatment effect	0.071	0.077	543	0.067	678	.868
Standard error	(0.030)**	(0.044)*		(0.040)*		
Comparison mean	4.811	4.814		4.808		
If employed: satisfaction with job(1-very unsatisfied-->5-very satisfied)(2019)						
Treatment effect	-0.195	-0.140	541	-0.237	745	.531
Standard error	(0.077)**	(0.120)		(0.100)**		
Comparison mean	3.750	3.761		3.742		
Actively searching for a job (2017)						
Treatment effect	0.095	0.113	997	0.073	972	.361
Standard error	(0.022)***	(0.030)***		(0.032)**		
Comparison mean	0.249	0.203		0.297		
Actively searching for a job (2019)						
Treatment effect	0.075	0.085	986	0.063	966	.619
Standard error	(0.022)***	(0.030)***		(0.032)**		
Comparison mean	0.242	0.198		0.288		
If no earnings and no school: actively searching for a job (2019)						
Treatment effect	0.083	0.062	467	0.097	242	.662
Standard error	(0.039)**	(0.047)		(0.067)		
Comparison mean	0.320	0.285		0.394		
If earnings: actively searching for a job (2019)						
Treatment effect	0.092	0.147	482	0.054	690	.082***
Standard error	(0.027)***	(0.039)***		(0.037)		
Comparison mean	0.197	0.115		0.254		
Panel G. Indirect and direct costs of secondary education						
Average monthly earnings between Jan 2009 and July 2012 (2013)						
Treatment effect	-7.781	-5.674	978	-10.066	961	.068***
Standard error	(1.200)***	(1.245)***		(2.055)***		
Comparison mean	12.562	9.238		16.027		
Average monthly earnings between Jan 2009 and Dec 2009 (2013)						
Treatment effect	-9.938	-7.004	984	-13.128	963	.041***
Standard error	(1.501)***	(1.617)***		(2.529)***		
Comparison mean	15.899	11.636		20.375		

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Average monthly earnings between Jan 2010 and Dec 2010 (2013)						
Treatment effect	-8.207	-6.378	991	-10.224	970	.177
Standard error	(1.425)***	(1.454)***		(2.454)***		
Comparison mean	12.340	9.046		15.788		
Average monthly earnings between Jan 2011 and Dec 2011 (2013)						
Treatment effect	-5.402	-4.577	991	-6.328	973	.516
Standard error	(1.346)***	(1.526)***		(2.221)***		
Comparison mean	9.781	7.906		11.735		
Average monthly earnings between Jan 2012 and Jul 2012 (2013)						
Treatment effect	-4.013	-4.005	996	-4.100	974	.972
Standard error	(1.365)***	(1.576)**		(2.225)*		
Comparison mean	8.695	7.341		10.110		

Notes: Year of survey in parentheses. Col. 1 shows results for the full sample, Col. 2 for females, Col. 3 for males. Col. 4 shows the p-values for tests that the effects are identical between males and females. The estimated treatment effects are in the first cell row; standard errors are in the second cell row in parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means are in the third cell row. No control variables included.

Table A3: Components of Indices

	All	Female		Male		P-value
	(1)	(2)	Obs	(3)	Obs	Female=Male
Panel A. Reading Test (2013)						
Able to read first sentence aloud when given document to read						
Treatment effect	0.037	0.038	1001	0.035	981	.939
Standard error	(0.014)***	(0.022)*		(0.017)**		
Comparison mean	0.876	0.851		0.902		
Read first paragraph aloud well or very well, as rated by surveyor						
Treatment effect	0.062	0.075	1001	0.044	980	.508
Standard error	(0.023)***	(0.033)**		(0.032)		
Comparison mean	0.503	0.432		0.577		
Basic comprehension						
Treatment effect	0.047	0.038	1001	0.053	981	.692
Standard error	(0.020)**	(0.029)		(0.026)**		
Comparison mean	0.728	0.686		0.771		
Fact identification						
Treatment effect	0.043	0.035	1001	0.050	981	.716
Standard error	(0.020)**	(0.029)		(0.027)*		
Comparison mean	0.740	0.719		0.762		
Intermediate comprehension						
Treatment effect	-0.001	0.022	1001	-0.025	980	.135
Standard error	(0.016)	(0.023)		(0.022)		
Comparison mean	0.128	0.116		0.140		
Advanced comprehension						
Treatment effect	0.047	0.047	1001	0.048	981	.981
Standard error	(0.023)**	(0.032)		(0.032)		
Comparison mean	0.333	0.349		0.316		
Panel B. Math Test (2013)						
Basic Computation 1						
Treatment effect	0.014	0.039	1002	-0.011	980	.036**
Standard error	(0.012)	(0.017)**		(0.018)		
Comparison mean	0.919	0.907		0.932		
Basic Computation 2						
Treatment effect	-0.005	-0.002	1002	-0.008	981	.794
Standard error	(0.011)	(0.015)		(0.017)		
Comparison mean	0.944	0.948		0.939		
Basic Calculator Computation (2013)						
Treatment effect	0.015	0.033	1002	-0.005	981	.328
Standard error	(0.019)	(0.029)		(0.025)		
Comparison mean	0.777	0.726		0.829		
Numeracy (2013)						
Treatment effect	0.028	0.026	1001	0.028	980	.946
Standard error	(0.016)*	(0.026)		(0.019)		
Comparison mean	0.850	0.806		0.897		
Profit calculation (easy)						
Treatment effect	0.006	0.025	1000	-0.014	981	.380
Standard error	(0.022)	(0.032)		(0.031)		
Comparison mean	0.650	0.622		0.680		
Profit calculation (difficult)						
Treatment effect	0.014	0.048	999	-0.022	978	.045**
Standard error	(0.017)	(0.023)**		(0.026)		
Comparison mean	0.151	0.108		0.196		

Identifying mode						
Treatment effect	0.036	0.036	1000	0.034	980	.927
Standard error	(0.012)***	(0.019)*		(0.015)**		
Comparison mean	0.907	0.887		0.928		
Calculating sums (without help)						
Treatment effect	-0.002	0.009	1000	-0.014	980	.502
Standard error	(0.018)	(0.023)		(0.026)		
Comparison mean	0.168	0.135		0.202		
Calculating sums (with explanation)						
Treatment effect	0.026	0.021	1000	0.030	981	.845
Standard error	(0.024)	(0.034)		(0.033)		
Comparison mean	0.556	0.538		0.576		
Calculating percentage						
Treatment effect	0.052	0.044	999	0.057	981	.737
Standard error	(0.019)***	(0.025)*		(0.029)*		
Comparison mean	0.192	0.149		0.237		
Applied Math Skills: Exchange rate calculation						
Treatment effect	0.071	0.084	999	0.053	981	.500
Standard error	(0.023)***	(0.033)**		(0.032)*		
Comparison mean	0.477	0.385		0.573		
Panel C. National Political Knowledge Standardized Score (2013)						
What is the name of the individual elected President of Ghana? (2013)						
Treatment effect	0.006	0.011	999	0.001	979	.632
Standard error	(0.010)	(0.015)		(0.014)		
Comparison mean	0.949	0.944		0.954		
What is the last name of the individual declared Vice President of Ghana? (2013)						
Treatment effect	0.010	0.026	700	-0.002	817	.493
Standard error	(0.020)	(0.031)		(0.026)		
Comparison mean	0.813	0.787		0.835		
Which political party was in power before the 2012 election in Ghana? (2013)						
Treatment effect	0.007	0.001	1000	0.013	979	.539
Standard error	(0.010)	(0.016)		(0.012)		
Comparison mean	0.950	0.941		0.960		
What is the last name of the presidential running mate for the NPP? (2013)						
Treatment effect	-0.001	-0.005	687	-0.002	812	.953
Standard error	(0.026)	(0.039)		(0.033)		
Comparison mean	0.660	0.606		0.706		
How many years can someone be legally elected president in Ghana? (2013)						
Treatment effect	0.018	0.056	962	-0.022	960	.086*
Standard error	(0.023)	(0.033)*		(0.031)		
Comparison mean	0.662	0.618		0.707		
What is the number of candidates that participated in the presidential elections						
Treatment effect	0.026	-0.002	813	0.047	859	.329
Standard error	(0.026)	(0.035)		(0.036)		
Comparison mean	0.413	0.337		0.486		
How many new constituencies were created for the 2012 general elections? (2013)						
Treatment effect	-0.020	0.008	471	-0.039	622	.298
Standard error	(0.023)	(0.029)		(0.035)		
Comparison mean	0.183	0.105		0.242		
Panel D. International Political Knowledge Standardized Score (2013)						
What is the last name of the current President of the United States? (2013)						
Treatment effect	-0.011	-0.036	1001	0.011	980	.116

Standard error	(0.015)	(0.026)		(0.014)		
Comparison mean	0.891	0.841		0.943		
What is the full name of the Secretary General of the United Nations? (2013)						
Treatment effect	0.011	-0.001	1001	0.017	979	.602
Standard error	(0.018)	(0.017)		(0.031)		
Comparison mean	0.175	0.071		0.285		
List all the countries that share a border with Ghana (2013)						
Treatment effect	0.038	0.023	1001	0.045	980	.636
Standard error	(0.023)	(0.032)		(0.033)		
Comparison mean	0.473	0.357		0.594		
Which country has the largest population in Africa? (2013)						
Treatment effect	0.056	-0.008	1000	0.110	980	.007***
Standard error	(0.024)**	(0.032)		(0.031)***		
Comparison mean	0.481	0.357		0.611		
What is the name of Venezuelas past president who died in March 2013? (2013)						
Treatment effect	0.005	0.000	1001	0.010	980	.474
Standard error	(0.007)	(0.004)		(0.013)		
Comparison mean	0.016	0.003		0.029		
Which country did Muamar Qaddafi lead? (2013)						
Treatment effect	0.032	0.033	1000	0.019	980	.747
Standard error	(0.023)	(0.031)		(0.030)		
Comparison mean	0.523	0.357		0.697		
What is the name of the leader from Cote DIvoire who the ICC is trying? (2013)						
Treatment effect	-0.022	0.001	1001	-0.051	979	.129
Standard error	(0.017)	(0.020)		(0.028)*		
Comparison mean	0.195	0.112		0.282		
Panel E. Media Engagement Index (2013)						
Number of days listened to radio in last 7 days						
Treatment effect	0.102	0.141	1001	0.035	980	.666
Standard error	(0.125)	(0.182)		(0.165)		
Comparison mean	3.861	3.409		4.332		
Number of days read newspaper in last 7 days						
Treatment effect	0.069	0.161	1001	-0.032	980	.055*
Standard error	(0.050)	(0.069)**		(0.074)		
Comparison mean	0.305	0.145		0.472		
Number of days watched TV in last 7 days						
Treatment effect	-0.018	-0.070	1001	0.033	980	.704
Standard error	(0.136)	(0.198)		(0.186)		
Comparison mean	3.500	3.490		3.511		
Number of days used internet in last 7 days						
Treatment effect	0.118	0.090	1001	0.114	980	.891
Standard error	(0.094)	(0.090)		(0.157)		
Comparison mean	0.804	0.304		1.326		
Has a newspaper that he/she prefers to read						
Treatment effect	-0.027	0.018	81	-0.041	309	.649
Standard error	(0.052)	(0.118)		(0.058)		
Comparison mean	0.601	0.431		0.646		
Panel F. ICT/Social Media Adoption Index (2017)						
Has Facebook account (2017)						
Treatment effect	0.053	0.078	997	0.014	973	.154
Standard error	(0.023)**	(0.033)**		(0.030)		
Comparison mean	0.553	0.408		0.706		

Has WhatsApp account (2017)						
Treatment effect	0.030	0.082	997	-0.027	973	.019**
Standard error	(0.023)	(0.033)**		(0.032)		
Comparison mean	0.572	0.489		0.659		
Panel G. Index of STI Exposure (2013)						
Do you do anything to protect yourself from getting infected with HIV/AIDs?						
Treatment effect	0.024	0.007	999	0.039	978	.339
Standard error	(0.017)	(0.028)		(0.019)**		
Comparison mean	0.836	0.783		0.892		
Have you had a sexually transmitted infection in past 12 months?						
Treatment effect	-0.022	-0.027	1000	-0.016	980	.681
Standard error	(0.013)*	(0.021)		(0.015)		
Comparison mean	0.096	0.129		0.062		
Has partner ever told you they had a sexually transmitted infection?						
Treatment effect	-0.006	0.003	1000	-0.015	980	.166
Standard error	(0.006)	(0.009)		(0.009)		
Comparison mean	0.023	0.016		0.031		
Did you change how often you had sex after learning partner infected with STI? (						
Treatment effect	-0.010	-0.212	18	-0.056	25	.762
Standard error	(0.358)	(0.548)		(0.212)		
Comparison mean	1.548	1.909		1.350		
Ever had sex (2013)						
Treatment effect	-0.028	0.015	1000	-0.066	980	.045**
Standard error	(0.021)	(0.024)		(0.032)**		
Comparison mean	0.766	0.845		0.685		
Age when first had sex (2013)						
Treatment effect	-0.012	-0.043	849	0.046	649	.710
Standard error	(0.113)	(0.120)		(0.208)		
Comparison mean	18.305	18.110		18.555		
Number of sexual partners in last 6 months (2013)						
Treatment effect	-0.071	-0.077	850	-0.064	649	.866
Standard error	(0.038)*	(0.039)**		(0.073)		
Comparison mean	0.699	0.708		0.688		
Number of sexual partners in lifetime (2013)						
Treatment effect	-0.322	-0.286	849	-0.353	648	.792
Standard error	(0.118)***	(0.133)**		(0.214)*		
Comparison mean	2.282	2.070		2.554		
Ever in a relationship with a partner >20 years older (2013)						
Treatment effect	-0.015	-0.032	1000	0.004	979	.125
Standard error	(0.012)	(0.021)		(0.012)		
Comparison mean	0.081	0.127		0.032		
Ever in a relationship for gifts or money (2013)						
Treatment effect	0.007	0.025	1000	-0.007	980	.388
Standard error	(0.019)	(0.031)		(0.021)		
Comparison mean	0.200	0.285		0.111		
Ever had sex with a commercial sex worker (2013)						
Treatment effect	-0.007	-0.001	1000	-0.013	965	.069*
Standard error	(0.003)*	(0.001)		(0.007)*		
Comparison mean	0.009	0.000		0.019		
Contraception last time had sex if ever had sex (2013)						
Treatment effect	0.070	0.044	848	0.110	649	.174
Standard error	(0.025)***	(0.035)		(0.034)***		

Comparison mean	0.652	0.609		0.706		
Ever used contraception if ever had sex (2013)						
Treatment effect	0.035	0.018	850	0.059	649	.345
Standard error	(0.022)	(0.030)		(0.031)*		
Comparison mean	0.776	0.766		0.789		
Panel H. Preventive Health Index (2013)						
Sleeps under an insecticide-treated mosquito net						
Treatment effect	0.028	0.041	1000	0.018	978	.633
Standard error	(0.024)	(0.033)		(0.033)		
Comparison mean	0.472	0.516		0.428		
Use any other method to protect yourself from mosquitos						
Treatment effect	0.044	0.032	1002	0.054	982	.634
Standard error	(0.024)*	(0.033)		(0.033)		
Comparison mean	0.457	0.439		0.475		
Used soap and water last time washed hands						
Treatment effect	0.034	0.035	998	0.035	979	.999
Standard error	(0.021)	(0.029)		(0.031)		
Comparison mean	0.699	0.742		0.653		
Panel I. Mental Health Index (2013)						
In the past few days did you ever... (Scale 1 to 5 (1=all of the time, 5=none of the time))						
feel bothered by things that usually do not bother you?						
Treatment effect	-0.000	-0.006	1001	0.005	980	.913
Standard error	(0.052)	(0.072)		(0.075)		
Comparison mean	3.838	3.847		3.829		
have trouble keeping your mind on what you were doing?						
Treatment effect	0.029	-0.050	1001	0.107	980	.139
Standard error	(0.054)	(0.074)		(0.077)		
Comparison mean	3.833	3.833		3.832		
feel depressed?						
Treatment effect	-0.025	-0.086	1001	0.034	980	.223
Standard error	(0.049)	(0.070)		(0.069)		
Comparison mean	3.983	3.965		4.003		
feel that everything you did was an effort?						
Treatment effect	-0.026	0.028	997	-0.077	974	.414
Standard error	(0.064)	(0.088)		(0.093)		
Comparison mean	3.156	3.188		3.122		
feel hopeful about the future?						
Treatment effect	-0.045	-0.029	1000	-0.060	978	.677
Standard error	(0.037)	(0.056)		(0.049)		
Comparison mean	1.488	1.521		1.454		
feel fearful?						
Treatment effect	-0.024	-0.003	1000	-0.050	977	.626
Standard error	(0.048)	(0.068)		(0.069)		
Comparison mean	4.238	4.143		4.337		
have restless sleep?						
Treatment effect	-0.009	0.034	1001	-0.053	980	.336
Standard error	(0.046)	(0.066)		(0.064)		
Comparison mean	4.307	4.261		4.355		

Notes: Year of survey in parentheses. Col. 1 shows results for the full sample, Col. 2 for females, Col. 3 for males. Col. 4 shows the p-values for tests that the effects are identical between males and females. The estimated treatment effects are in the first cell row; standard errors are in the second cell row in parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means are in the third cell row. No

Table A4: P-values and Sharpened q-values

Table	Variable	Combined		
		All	Female	Male
		(1)	(2)	(3)
	Total years of education to date (2017)			
	p-value	0.000***	0.000***	0.000***
	sharpened q-value	0.001***	0.001***	0.001***
	Total standardized score (2013)			
	p-value	0.001***	0.005***	0.056*
	sharpened q-value	0.002***	0.020**	0.086*
	Labor Index (2017)			
	p-value	0.001***	0.010**	0.054*
	sharpened q-value	0.003***	0.030**	0.086*
	Number of children ever had (2017)			
	p-value	0.004***	0.011**	0.399
	sharpened q-value	0.009***	0.032**	0.324
	Preventative health behavior (3 questions) (2013)			
	p-value	0.004***	0.029**	0.052*
	sharpened q-value	0.009***	0.059*	0.086*
	Job with benefits in private sector (2017)			
	p-value	0.030**	0.161	0.110
	sharpened q-value	0.029**	0.174	0.137
	Total hours worked last month (if worked at least 10 hours) (2017)			
	p-value	0.767	0.658	0.992
	sharpened q-value	0.238	0.464	0.569
	Has a bank account (2013)			
	p-value	0.011**	0.002***	0.659
	sharpened q-value	0.017**	0.008***	0
	Knows how to use the internet (2013)			
	p-value	0.069*	0.374	0.133
	sharpened q-value	0.050*	0.322	0
	Uses fertilizer (conditional on farming) (2017)			
	p-value	0.527	0.720	0.232
	sharpened q-value	0.163	0.497	0
	Migrated to an urban area (2017)			
	p-value	0.272	0.342	0.518
	sharpened q-value	0.112	0.310	0
	Ever lived with partner (married/cohabiting) (2013)			
	p-value	0.008***	0.056*	0.063*
	sharpened q-value	0.013**	0.086*	0
	Ever lived with partner(2016)			
	p-value	0.000***	0.000***	0.042**
	sharpened q-value	0.001***	0.002***	0
	Currently living with partner (2017)			
	p-value	0.239	0.296	0.704
	sharpened q-value	0.104	0.280	0

Table A4: P-values and Sharpened q-values

Table	Variable	Combined		
		All	Female	Male
		(1)	(2)	(3)
	Most recent partner completed tertiary program (2017)			
	p-value	0.197	0.013**	0.279
	sharpened q-value	0.090*	0.035**	0
	Ever enrolled in senior high school (2017)			
	p-value	0.000***	0.000***	0.000***
	sharpened q-value	0.001***	0.001***	0
	Completed SHS (2017)			
	p-value	0.000***	0.000***	0.000***
	sharpened q-value	0.001***	0.001***	0
	Completed TVI (2017)			
	p-value	0.000***	0.275	0.000***
	sharpened q-value	0.001***	0.270	0
	Completed apprenticeship (2017)			
	p-value	0.000***	0.003***	0.001***
	sharpened q-value	0.001***	0.013**	0
	Currently enrolled in tertiary program (2017)			
	p-value	0.096*	0.012**	0.865
	sharpened q-value	0.056*	0.034**	0
	Ever enrolled in tertiary program (2017)			
	p-value	0.009***	0.003***	0.455
	sharpened q-value	0.015**	0.014**	0
	Completed tertiary			
	p-value	0.175	0.353	0.328
	sharpened q-value	0.085*	0.312	0
	Admitted to a tertiary program (2017)			
	p-value	0.001***	0.000***	0.204
	sharpened q-value	0.002***	0.002***	0
	Standardized score Reading test (2013)			
	p-value	0.001***	0.022**	0.026**
	sharpened q-value	0.004***	0.051*	0
	Standardized score Math test (2013)			
	p-value	0.007***	0.011**	0.265
	sharpened q-value	0.013**	0.031**	0
	National political knowledge standardized score (2013)			
	p-value	0.031**	0.048**	0.356
	sharpened q-value	0.030**	0.082*	0
	International political knowledge standardized score (2013)			
	p-value	0.157	0.899	0.113
	sharpened q-value	0.077*	0.556	0

Table A4: P-values and Sharpened q-values

		Combined		
		All	Female	Male
Table	Variable	(1)	(2)	(3)
	Index of Internet Use (2013)			
	p-value	0.105	0.360	0.232
	sharpened q-value	0.060*	0.312	0
	Social Media Adoption Index (2017)			
	p-value	0.041**	0.007***	0.807
	sharpened q-value	0.035**	0.022**	0
	Index of risky sexual behavior/STI exposure (safe --> risky) (2013)			
	p-value	0.040**	0.645	0.025**
	sharpened q-value	0.035**	0.462	0
	Media engagement (radio newspaper TV internet) (2013)			
	p-value	0.018**	0.017**	0.346
	sharpened q-value	0.023**	0.042**	0
	Ever pregnant/had a pregnant partner (2017)			
	p-value	0.063*	0.028**	0.971
	sharpened q-value	0.049**	0.059*	0
	Had unwanted first pregnancy (full sample) (2013)			
	p-value	0.024**	0.043**	0.496
	sharpened q-value	0.027**	0.080*	0
	Desired fertility: # of children by age 50 (2013)			
	p-value	0.609	0.531	0.896
	sharpened q-value	0.184	0.399	0
	Total earnings in past 6 months (including owed wages) (2017)			
	p-value	0.429	0.529	0.811
	sharpened q-value	0.150	0.399	0
	Log earnings in past 6 months (including owed wages) (2017)			
	p-value	0.194	0.188	0.833
	sharpened q-value	0.090*	0.199	0
	Public sector wage employee (2017)			
	p-value	0.002***	0.005***	0.101
	sharpened q-value	0.004***	0.019**	0
	Self-employed (2017)			
	p-value	0.012**	0.009***	0.468
	sharpened q-value	0.018**	0.028**	0
	Job with benefits (2017)			
	p-value	0.003***	0.034**	0.044**
	sharpened q-value	0.007***	0.067*	0

Notes: Year of survey in parentheses. See Table 2 notes for description of columns; Cell row 1 shows the p-value for the sharpened form estimate of the treatment effect; cell row 2 shows the sharpened q values, which account for false discovery rate (Benjamini, Krieger, and Yekutieli, 2006; ***, **, * indicating significance at 1, 5 and 10%; all regressions control for region fixed effects, JHS finishing exam score (BECE) and missing JHS finishing exam scores.

Table A5: Comparing Compliers and Always-Takers

	All	Female		Male		P-value
	(1)	(2)	Obs	(3)	Obs	Female=Male
Age in 2008 (2008)						
Treatment effect	0.205	0.308	495	0.119	595	.277
Standard error	(0.088)**	(0.125)**		(0.122)		
Comparison mean	16.940	16.767		17.085		
Completed BECE in 2007 (2008)						
Treatment effect	0.037	0.082	497	-0.001	595	.022**
Standard error	(0.018)**	(0.036)**		(0.003)		
Comparison mean	0.073	0.159		0.000		
BECE exam performance (2008)						
Treatment effect	-0.000	0.000	466	0.000	555	.
Standard error	(0.000)	(0.000)***		(0.000)***		
Comparison mean	0.633	0.630		0.636		
BECE performance data missing (2008)						
Treatment effect	-0.000	-0.000	497	0.000	595	.
Standard error	(0.000)	(0.000)		(0.000)		
Comparison mean	0.053	0.054		0.052		
Admitted to academic major						
Treatment effect	0.014	-0.022	481	0.044	585	.283
Standard error	(0.030)	(0.045)		(0.041)		
Comparison mean	0.418	0.457		0.386		
Female						
Treatment effect	-0.001	-0.000	497	0.000	595	.
Standard error	(0.030)	(0.000)***		(0.000)		
Comparison mean	0.456	1.000		0.000		
No male head in the household (2008)						
Treatment effect	0.011	-0.011	497	0.029	593	.510
Standard error	(0.030)	(0.045)		(0.041)		
Comparison mean	0.421	0.435		0.410		
Number of HH members (2008)						
Treatment effect	-0.035	-0.048	497	-0.025	593	.936
Standard error	(0.146)	(0.203)		(0.209)		
Comparison mean	5.686	5.645		5.720		
Years of education of HH head (2008)						
Treatment effect	-0.294	-0.546	496	-0.086	591	.484
Standard error	(0.328)	(0.483)		(0.446)		
Comparison mean	6.010	6.331		5.742		
Highest education of HH head: tertiary (2008)						
Treatment effect	-0.015	-0.032	496	-0.001	591	.248
Standard error	(0.013)	(0.020)		(0.018)		
Comparison mean	0.063	0.076		0.052		
Perceived returns to SHS (%) (2008)						
Treatment effect	23.694	39.579	421	11.306	520	.713
Standard error	(38.390)	(55.327)		(53.316)		
Comparison mean	294.774	301.417		289.307		
Perceived returns to SHS education>100% (2008)						
Treatment effect	0.019	0.004	421	0.031	520	.681
Standard error	(0.033)	(0.049)		(0.044)		
Comparison mean	0.478	0.506		0.455		
Ever had sex (2008)						
Treatment effect	-0.002	0.004	496	-0.005	595	.860

Standard error	(0.025)	(0.042)		(0.029)		
Comparison mean	0.226	0.330		0.140		
Standardized score, Reading test (2013)						
Treatment effect	-0.052	-0.108	483	-0.006	581	.219
Standard error	(0.042)	(0.062)*		(0.056)		
Comparison mean	0.452	0.499		0.412		
Standardized score, Math test (2013)						
Treatment effect	0.012	0.053	483	-0.021	581	.486
Standard error	(0.053)	(0.081)		(0.069)		
Comparison mean	0.333	0.221		0.426		
Total standardized score (2013)						
Treatment effect	-0.020	-0.022	483	-0.017	581	.954
Standard error	(0.046)	(0.071)		(0.060)		
Comparison mean	0.455	0.407		0.495		
Yearly HH Expenditure (2008)						
Treatment effect	192.718	208.087	495	179.940	593	.918
Standard error	(134.332)	(186.416)		(195.823)		
Comparison mean	2590.645	2542.274		2631.076		
House walls made of mud, wood, plastic or iron (2008)						
Treatment effect	-0.023	-0.015	496	-0.029	593	.818
Standard error	(0.030)	(0.043)		(0.041)		
Comparison mean	0.443	0.409		0.471		
House roof made of mud or thatch (2008)						
Treatment effect	0.000	0.000	494	0.000	591	.
Standard error	(0.000)	(0.000)		(0.000)		
Comparison mean	0.000	0.000		0.000		
Number of rooms in house (2008)						
Treatment effect	0.034	0.064	489	0.009	578	.859
Standard error	(0.152)	(0.238)		(0.197)		
Comparison mean	3.034	3.063		3.009		
Toilet in house (2008)						
Treatment effect	-0.015	0.009	472	-0.034	556	.491
Standard error	(0.031)	(0.045)		(0.042)		
Comparison mean	0.411	0.400		0.420		
Member of HH went to bed hungry in last month (2008)						
Treatment effect	0.053	0.023	497	0.079	590	.159
Standard error	(0.021)***	(0.028)		(0.029)***		
Comparison mean	0.099	0.098		0.101		
Meal with no meat or fish because no money in last month (2008)						
Treatment effect	0.007	0.038	492	-0.018	588	.238
Standard error	(0.024)	(0.033)		(0.034)		
Comparison mean	0.187	0.136		0.229		
Self-reported financial situation (1-very comfortable-->5-very poor)(2008)						
Treatment effect	0.069	0.073	497	0.065	587	.916
Standard error	(0.042)	(0.061)		(0.057)		
Comparison mean	3.854	3.786		3.911		
Ever enrolled in tertiary program (2017)						
Treatment effect	-0.023	0.024	480	-0.061	574	.105
Standard error	(0.026)	(0.039)		(0.035)*		
Comparison mean	0.251	0.231		0.268		

Notes: Year of survey in parentheses. Col. 1 shows results for the full sample, Col. 2 for females, Col. 3 for males. Col. 4 shows the p-values for tests that the effects are identical between males and females. The estimated treatment effects are in the first cell row; standard errors are in the second cell row in parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means are in the third cell row. No

Table A6: Initial Majors and Switching (Control Group)

	All	Female	Male	P-val
	Mean	Mean	Mean	Male =
	(Std. Dev.)	(Std. Dev.)	(Std. Dev.)	Female
	(1)	(2)	(3)	(4)
Panel A. Academic Majors				
Admitted to Academic Major	0.407	0.420	0.395	.378
	(0.491)	(0.494)	(0.489)	
Admitted to General Arts	0.374	0.394	0.354	.115
	(0.484)	(0.489)	(0.478)	
Admitted to General Science	0.033	0.025	0.041	.067*
	(0.179)	(0.157)	(0.198)	
Ever Enrolled in SHS (% of admitted to academic)	0.574	0.532	0.619	.044**
	(0.495)	(0.500)	(0.487)	
Switched to Vocational Major (% of ever enrolled)	0.261	0.222	0.295	.224
	(0.440)	(0.417)	(0.457)	
Panel B. Vocational Majors				
Admitted to Vocational Major	0.593	0.580	0.605	.378
	(0.491)	(0.494)	(0.489)	
Admitted to Business	0.213	0.170		0.000***
	(0.410)	(0.376)	(0.438)	
Admitted to Home Economics	0.155	0.287	0.020	0.000***
	(0.362)	(0.453)	(0.139)	
Admitted to Agriculture	0.114	0.082	0.147	0.000***
	(0.318)	(0.274)	(0.355)	
Admitted to Technology	0.060	0.013	0.108	0.000***
	(0.238)	(0.115)	(0.310)	
Admitted to Visual Arts	0.050	0.028	0.073	0.000***
	(0.219)	(0.166)	(0.260)	
Ever Enrolled in SHS (% of admitted to vocational)	0.555	0.490	0.619	0.000***
	(0.497)	(0.501)	(0.486)	
Switched to Academic Major (% of ever enrolled)	0.381	0.426	0.347	.094*
	(0.486)	(0.496)	(0.477)	
Observations	1331	672	659	

Notes: Data for "Admitted to..." from 2008 baseline survey. "Switching to..." variables constructed by comparing 2008 baseline track with track recorded in 2013 follow-up. Data for "Ever Enrolled in SHS..." from 2016 follow-up. Columns 1, 2, and 3: control group means with standard errors presented below in parentheses, with ***, **, * indicating significance at 1, 5 and 10%.; Column 4: the p-value on a test of whether control group means for females and males are equal.

Table A7: Academic Major Admits vs. Vocational Major Admits

	Academic Major Admits			Vocational Major Admits		
	All	Female	Male	All	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Total standardized score (2013)						
Treatment effect	0.155	0.261	0.036	0.125	0.113	0.130
Standard error	(0.069)**	(0.102)**	(0.092)	(0.062)**	(0.094)	(0.077)*
Comparison mean	0.083	-0.090	0.267	-0.017	-0.188	0.155
	(2)=(3)=(5)=(6): .437	(2)=(3): .101		(1)=(4): .743	(5)=(6): .888	
Number of children ever had (2017)						
Treatment effect	-0.149	-0.232	-0.019	-0.120	-0.176	-0.035
Standard error	(0.067)**	(0.108)**	(0.075)		(0.102)*	(0.060)
Comparison mean	0.719	0.978	0.433	0.752	1.152	0.348
p-value on equality of effects	(2)=(3)=(5)=(6): .251	(2)=(3): .106		(1)=(4): .757	(5)=(6): .231	
Preventative health behavior (3 questions) (2013)						
Treatment effect	0.142	0.160	0.139	0.085	0.094	0.078
Standard error	(0.057)**	(0.085)*	(0.075)*	(0.050)*	(0.070)	(0.071)
Comparison mean	1.621	1.703	1.534	1.613	1.674	1.551
p-value on equality of effects	(2)=(3)=(5)=(6): .862	(2)=(3): .857		(1)=(4): .449	(5)=(6): .867	
Index of Internet Use (2013)						
Treatment effect	0.003	-0.062	0.028	0.095	0.104	0.079
Standard error	(0.059)	(0.070)	(0.086)	(0.048)*	(0.060)*	(0.071)
Comparison mean	0.042	`	0.288	-0.015	-0.244	0.214
p-value on equality of effects	(2)=(3)=(5)=(6): .311	(2)=(3): .419		(1)=(4): .227	(5)=(6): .786	
Ever enrolled in tertiary program (2017)						
Treatment effect	0.073	0.137	0.010	0.020	0.016	0.023
Standard error	(0.029)**	(0.042)***	(0.039)	(0.021)	(0.027)	(0.032)
Comparison mean	0.129	0.106	0.154	0.116	0.096	0.137
p-value on equality of effects	(2)=(3)=(5)=(6): .076*	(2)=(3): .027***		(1)=(4): .141	(5)=(6): .866	
Labor Index (2017)						
Treatment effect	0.081	0.147	-0.014	0.118	0.070	0.151
Standard error	(0.046)*	(0.064)**	(0.064)	(0.040)***	(0.055)	(0.053)***
Comparison mean	0.014	-0.158	0.203	-0.008	-0.154	0.140
p-value on equality of effects	(2)=(3)=(5)=(6): .179	(2)=(3): .073**		(1)=(4): .534	(5)=(6): .288	
Currently enrolled in tertiary program (2017)						
Treatment effect	0.052	0.091	0.017	-0.000	0.019	-0.020
Standard error	(0.024)**	(0.036)**	(0.032)	(0.017)	(0.023)	(0.025)
Comparison mean	0.077	0.070	0.085	0.075	0.056	0.094
p-value on equality of effects	(2)=(3)=(5)=(6): .094*	(2)=(3): .122		(1)=(4): .072*	(5)=(6): .237	
Positive earnings in past 6 months (including owed wages) (2017)						
Treatment effect	0.049	0.050	0.028	0.037	-0.011	0.074
Standard error	(0.035)	(0.054)	(0.041)	(0.029)	(0.045)	(0.033)**
Comparison mean	0.688	0.576	0.811	0.703	0.616	0.791
p-value on equality of effects	(2)=(3)=(5)=(6): .475	(2)=(3): .752		(1)=(4): .780	(5)=(6): .124	
Public sector wage employee (2017)						
Treatment effect	0.028	0.033	0.023	0.038	0.050	0.027
Standard error	(0.016)*	(0.022)	(0.024)	(0.014)***	(0.021)**	(0.018)
Comparison mean	0.029	0.018	0.040	0.024	0.024	0.024
p-value on equality of effects	(2)=(3)=(5)=(6): .803	(2)=(3): .759		(1)=(4): .649	(5)=(6): .389	
Self-employed (2017)						
Treatment effect	-0.035	-0.093	0.026	-0.058	-0.062	-0.049
Standard error	(0.031)	(0.044)**	(0.042)	(0.027)**	(0.041)	(0.035)
Comparison mean	0.221	0.268	0.169	0.276	0.332	0.218
p-value on equality of effects	(2)=(3)=(5)=(6): .240	(2)=(3): .052**		(1)=(4): .583	(5)=(6): .799	
Job with benefits (2017)						
Treatment effect	0.029	0.039	0.017	0.065	0.054	0.074
Standard error	(0.023)	(0.032)	(0.034)	(0.021)***	(0.027)**	(0.032)**
Comparison mean	0.087	0.070	0.105	0.083	0.066	0.100
p-value on equality of effects	(2)=(3)=(5)=(6): .654	(2)=(3): .635		(1)=(4): .251	(5)=(6): .631	
Total hours worked last month (if worked at least 10 hours)						
Treatment effect	3.646	12.927	-2.944	-4.384	-13.709	1.422
Standard error	(9.542)	(14.798)	(12.534)	(7.943)	(12.438)	(10.248)
Comparison mean	143.848	141.205	145.929	152.140	159.964	147.078
p-value on equality of effects	(2)=(3)=(5)=(6): .569	(2)=(3): .413		(1)=(4): .516	(5)=(6): .346	
Total earnings in past 6 months (including owed wages) (2017)						
Treatment effect	41.000	196.867	-181.972	79.970	-68.960	193.482
Standard error	(123.272)	(148.540)	(191.932)	(100.826)	(116.756)	(153.378)
Comparison mean	1113.520	672.992	1598.471	1140.298	820.063	1465.886
p-value on equality of effects	(2)=(3)=(5)=(6): .226	(2)=(3): .119		(1)=(4): .807	(5)=(6): .172	
Log earnings in past 6 months (including owed wages) if positive earnings (2017)						
Treatment effect	-0.030	0.077	-0.134	0.146	0.134	0.113
Standard error	(0.113)	(0.185)	(0.138)	(0.082)*	(0.132)	(0.099)
Comparison mean	6.812	6.460	7.088	6.829	6.522	7.072
p-value on equality of effects	(2)=(3)=(5)=(6): .460	(2)=(3): .360		(1)=(4): .209	(5)=(6): .896	

Notes: Year of survey in parentheses. Col. 1 shows results for all academic major admits, Col. 2 for female academic major admits, Col. 3 for male academic major admits, Col. 4 for all vocational major admits, Col. 5 for female vocational majors and Col. 6 for male vocational major admits. The estimated treatment effects are in the first cell row; standard errors are in the second cell row in parentheses, with ***, **, * indicating significance at 1, 5 and 10%; comparison group means are in the third cell row; the fourth cell row reports p-values of tests of hypotheses of equality of treatment effects between the columns specified in parentheses; all regressions control for region fixed effects, JHS finishing exam score (BECE) and missing JHS finishing exam scores.