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Abstract

Covering the full population of applicants to the Jamaican Conditional Cash Transfer Program (PATH), we explore whether receiving PATH benefits alters the academic returns to subsequently attending a more preferred public secondary school. To uncover causal associations, we exploit exogenous variation arising from both the PATH eligibility criteria and the centralized allocation process to public secondary schools within a double regression discontinuity design. Among girls, receiving PATH benefits before secondary school enrollment does not influence the academic gains from attending a more selective school. However, boys exposed to PATH experience significantly lower returns to subsequently attending a more selective school with respect to comparable peers who did not receive PATH. These results highlight the relevance of considering both the direct effects of conditional cash transfers and the potential indirect effects that such policies could convey through altering the effectiveness of other related policies. [1]

JEL Codes: H52, H75, I21, I26, I28, I38

Keywords: academic performance, conditional cash transfers, school selectivity, Jamaica.

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1 Introduction

Conditional cash transfers (CCT) are fundamental components of social protection policies in Latin America and the Caribbean (Fiszbein and Schady, 2009; Stampini and Tornarolli, 2012; Paes-sousa et al., 2013; Ibarrarán et al., 2013). They also operate in several developing countries in Asia and Africa, as well as in some high income countries, including the United States. With their dual objective of (a) alleviating current poverty and (b) fostering demand for health and education services (through conditioning the monetary transfers to school attendance and regular medical screenings); they seek to alter households' incentives to increase human capital of children in ways that may improve long-term productivity. Therefore, CCTs do not operate within a vacuum but interact with other human capital development interventions, of which they could alter the effectiveness. Using administrative data covering the full population of applicants to the Jamaica's CCT Programme of Advancement through Health and Education (PATH), we investigate whether benefiting from PATH since childhood altered the academic returns to attending a more preferred or selective secondary school.[2]

Existing evidence consistently documents positive effects of CCTs on school attendance (Attanasio et al., 2011; Baird et al., 2013; Parker and Todd, 2017; Schultz, 2004; Todd and Wolpin, 2006). Evidence on learning effects is relatively scarcer and mixed ranging from null (Araujo et al., 2017; Baez and Camacho, 2011) to positive (Barham et al., 2013; Stampini et al., 2018). More recent studies explore the effects of CCTs on longer-term educational attainment and labor market outcomes among individuals who were treated during childhood (Araujo and Macours, 2021; Attanasio et al., 2021; Barham et al., 2017, 2018; Parker and Vogl, 2021; Molina Millán et al., 2020).[3] While these important studies analyze the direct effects of CCTs, there is no evidence on whether CCTs might alter the effectiveness of other related interventions. Our study contributes to filling this knowledge gap.

Investigating this question requires exogenous variation on participation in both CCTs and other interventions, as well as longitudinal data tracking the outcomes of interest of beneficiaries and non-beneficiaries. We exploit exogenous variation within the eligibility criteria of Jamaica's PATH as well as subsequent exogenous variation within the centralized assignment process to public secondary schools. We explore whether PATH beneficiaries experienced differential returns from subsequently attending more selective secondary schools. We observe the full population of PATH applicants between its inception in 2001 and 2013, tracing them over time up to post-secondary studies. Our main outcomes of interest comprise performance on end of secondary and post-

[2]These potential interactions between different policies are also related to the hypothesis that skills might beget skills (Cunha and Heckman, 2007). Under this hypothesis, for example, beneficiaries of CCTs during childhood who experienced positive effects on early learning might benefit more from later education-related interventions (i.e., positive complementarities).

[3]For a comprehensive review of CCT's long-term impacts, see Molina Millán et al. (2019).

secondary high stakes examinations independently administered by the Caribbean Examinations Council.

For both boys and girls, we document null direct effects of PATH on learning at the end of secondary school or on post-secondary certifications. We also find that both boys and girls significantly benefit from attending more selective schools. For girls, the returns to selective school attendance are similar for those who benefited from PATH and comparable peers who did not receive PATH. However, among boys, the returns to selective school attendance are significantly lower for those who were PATH beneficiaries with respect to comparable counterparts who did not benefit from PATH. Overall, our findings highlight the relevance of considering not only the direct effects of CCTs, but also potential indirect effects that could operate through altering the effectiveness of other interventions.

Our work is related to studies that have examined interaction effects between different exogenous shocks or interventions (Adhvaryu et al., 2020; Bhalotra and Venkataramani, 2015; Gilraine, 2018; Goff et al., 2022; Johnson and Jackson, 2019; Rossin-Slater and Wust, 2020; Mbiti et al., 2019). We contribute to this literature by providing the first evidence of interactions between CCTs and another related human capital development intervention – accessibility to a more selective and effective school. The remainder of the paper is organized as follows. Section 2 summarizes the Jamaican context. Section 3 presents the data and summary statistics. Section 4 lays out the empirical strategy used to isolate the causal effects of both interventions and their interactions. Section 5 presents our results and their discussion. Section 6 concludes.

2 The Jamaican Context

2.1 The Programme of Advancement through Health and Education (PATH)

PATH targets households in the bottom two quintiles of the income distribution, with the dual aim of alleviating their current poverty (through income support) and developing children's human capital (through health and education conditionalities). It was launched in 2001 with a one-year pilot in the parish of St. Catherine, after which it was rolled out to the entire country.[4] To date, it has about 350,000 beneficiary households.

Enrollment is demand driven. A household representative starts the application process at a Parish Office, where s/he completes a socioeconomic form. This information is used to compute a poverty proxy means test (PMT) score. The PMT formula is unknown to applicants, making it very difficult to game.[5] Applicant households with a score under the predetermined eligibility threshold are declared eligible. Applicants exceeding the threshold by less than five points enter an

[4] A parish is a geopolitical area that has its own local government arrangements. Jamaica is divided into 14 parishes.

[5] We were granted access to the PATH applications databases and the PMT score of each applicant. However, the formula used to obtain the score was not revealed.

automatic appeal process. Although applicants exceeding the threshold by more than five points do not enter an automatic appeal, they can appeal on their own initiative. A social worker visits appealing households and collects updated information that is used to calculate a rectified PMT score. For all our empirical work, we use the initial formula-based score as the running variable for PATH eligibility as it is calculated homogeneously for all applicants.

Once a family is declared eligible, it starts receiving transfers, which are paid every two months. The education component is conditioned on children attending at least 85% percent of school days. Compliance is verified through information provided by the schools to the program (Levy and Ohls, 2010). The education transfer is granted to each eligible child until the completion of secondary school, and the amount differs by the age of the child. The amounts have varied over time to account for inflation, and between 2012 and 2015 they also varied by the gender of the child (with boys receiving transfers 10 percent higher than girls). On average, the per-child monthly transfer has represented about 9 percent of the prevailing monthly full-time minimum wage.[6]

2.2 The Education System

At the end of primary school, students register to take the Grade Six Achievement Test (GSAT) and provide a list of ranked secondary school choices to the Ministry of Education, Youth, and Information (MOEY).[7] There were 468 public secondary schools to which students were allocated between 2003 and 2015. The GSAT is comprised of five subjects that all students take: mathematics, science, language arts, social studies, and communication tasks. The MOEY ranks students by their GSAT overall score and gender. No other criteria are used (e.g., sibling preferences or geographic proximity). Individual school capacity by gender is predetermined. The algorithm assigns the highest-ranked student to her first choice. It then moves on to the second and treats her similarly. The procedure continues until it reaches a student whose first choice is full. At that point, it tries to assign the student to her second choice. If full, to the third choice and so on. Once this student has been assigned to a school, the algorithm moves on to the next person.

Under the assignment mechanism, as the number of school choices is constrained, students may have an incentive to exclude some desirable schools from their list if the probability of ad-

[6]In 2006, the value of the education transfer amounted to J$ 600 (about US$ 10) per month per child. Later, the value was differentiated by grade and sex of the beneficiary. For example, in 2012, girls in grades 1–6 (primary), 7–9 (lower secondary) and 10–13 (upper secondary) received J$ 750 (US$ 8.4), J$ 975 (US$ 11) and J$ 1150 (US$ 12.9) per month, respectively; the transfers for boys were 10% higher, at J$ 825 (US$ 9.3), J$ 1075 (US$ 12.1) and J$ 1265 (US$ 14.2) per month, respectively (in 2012, J$ 88.99 = US$ 1). In 2015, the differentiation by sex was removed; the education transfer amounted to J$ 1045 (US$ 9), J$ 1400 (US$ 12) and J$ 1600 (US$ 13.8) for primary, lower secondary and upper secondary children, respectively, irrespective of their sex (in 2015, the average exchange rate was J$ 116.28 = US$ 1). In 2017, the education transfer amounted to J$ 1350 (US$ 10.5), J$ 1800 (US$ 14) and J$ 2100 (US$ 16.4) for primary, lower secondary and upper secondary children, respectively, irrespective of their sex (in 2017, the average exchange rate was J$ 128.30 = US$ 1).

[7]The list of ranked schools is submitted before taking the GSAT. Between 2003 and 2004, students could rank up to three school choices. Between 2005 and 2015, students could rank up to five school choices.

mission is too low (Haeringer and Klijn, 2009; Beuermann et al., 2021). However, among the set of schools listed, it is a dominant strategy to list them in order of true preference (Roth and Oliveira Sotomayor, 1990). Accordingly, so long as parents make rational choices, one can infer that a higher-ranked school is preferred to a lower-ranked school. As shown in Section 3, parents consistently rank schools with higher average incoming GSAT scores higher. As the assignment mechanism determines that highest-achieving students are admitted to their top choices first, a preferred school is virtually synonymous with being more selective or more academically elite.

All secondary schools teach a homogeneous national curriculum. Secondary school begins in first form (the equivalent of 7th grade) and ends at fifth form (the equivalent of 11th grade) when students take the Caribbean Secondary Education Certification (CSEC) examinations. These are equivalent to the British Ordinary levels examinations and are externally graded by the Caribbean Examinations Council (CXC). The CSEC examinations are given in 37 subjects. Passing five subjects (including English and mathematics) is a sufficient entry requirement for community colleges, technical schools, or training schools. It can also be used for entry at some colleges in the United States. Students who complete these requirements could either continue their studies at a tertiary institution (if accepted) or pursue the Caribbean Advanced Proficiency Examination (CAPE), also externally graded by CXC.

The CAPE is a tertiary-level program. Students seeking to attend university (as opposed to a community college) take the CAPE. The CAPE is equivalent to the British Advanced levels examinations. The CAPE is a two-year program and includes two core units (Caribbean and Communication Studies) and six other units. Passing at least two CAPE units is typically required for entry to the University of the West Indies. Passing six CAPE units is a common admission requirement to British higher education institutions. The post-secondary qualification of a CAPE Associate Degree is awarded after passing seven CAPE units (including the core units).

3 The Data and Summary Statistics

We observe the full population of households who applied to the PATH between its inception in 2001 and 2013. Among these, we focus on those households with at least one member who: (i) was younger than 11 at the time of application (as students typically take the GSAT and enroll in secondary school at 11–12 years old); and (ii) belongs to year of birth cohorts that allow sufficient time to reach the age of CSEC/CAPE taking by 2020 (which is the most recent data available). This because we seek to study potential effects of PATH and subsequent attendance to preferred secondary schools on CSEC/CAPE outcomes. As students enroll in secondary school at 11–12 years old, our relevant sample includes those who were below this age threshold at PATH application and with enough age to observe the outcomes of interest within our data. This delivers 280,888 individual-level observations.

We then merged the PATH data with the official administrative GSAT data from 2003 until 2015. In the absence of individual identifiers, the data were linked by full name, gender, and date of birth. We matched 78.4% of PATH applicants to the GSAT records. This closely mimics the 78.7% official statistic of school age children enrolled in primary school.[8] This suggests that our match rate is not an artifact of our methodology but reflects the true primary school enrollment rate.[9] The matched data comprise 220,092 individual-level observations of which 113,140 are girls and 106,952 are boys.[10] These data include the parish of residence, the gender and educational attainment of the adult who filed the PATH application, household income, home ownership status, household size, the PMT score, the PMT eligibility cutoff, whether the household actually received PATH benefits, the individual-level GSAT performance and the ranked list of secondary schools the student wished to attend.

To track the outcomes of interest, we collected population data on the CSEC examinations between 2005 and 2020; as well as population data on the CAPE examinations between 2009 and 2020. Both the CSEC and CAPE data contain scores for each subject examination taken. The CSEC and CAPE data were linked at the individual level to the GSAT data.[11] Notice that since the CAPE is completed seven years after the GSAT and the most recent CAPE data is 2020, then the last relevant GSAT cohort for these outcomes is 2013. By similar logic, since the CSEC is completed 5 years after GSAT and the most recent CSEC data is 2020, then the last relevant GSAT cohort for these outcomes is 2015.

Table 1 reports summary statistics. The average individual was 80 months old at the time of PATH application. About 86% of household representatives applying to the program were female; 38% of them had completed secondary education. Household weekly income was about PPP US$ 25.7 (equivalent to 23% of the prevailing weekly full-time minimum wage).[12] About 42% report owning the dwelling; households had on average 5.7 members. About half of applicants ended up receiving PATH benefits.

The average student took the GSAT at 143 months of age. Girls score about 0.46 sd higher than boys in the GSAT and attend more selective schools, with 0.27 sd higher in incoming peer GSAT scores than those attended by the average boy. We measure the selectivity of school choices by computing the average GSAT standardized score of students assigned to each school choice. While

[8] Source: World Development Indicators Database (https://databank.worldbank.org/source/world-development-indicators). Country: Jamaica. Year: 2013.

[9] As an additional check, we computed the ratio of the total number of individuals in the GSAT database aged 10–12 by the census date (April 4th, 2011) divided by the population aged 10–12 counted in the census. This exercise delivers an implied GSAT taking rate of 80.2% which is in line with our PATH-GSAT match rate.

[10] See Appendix Table A.1 for a sample breakdown by year of birth and PATH application year.

[11] The full population GSAT data was linked to the CSEC/CAPE data by full name, gender, and date of birth. 92% of CSEC and 96% of CAPE observations were matched to the GSAT data. The 4-8% of unmatched observations closely mimics the 6% enrollment rate in private secondary schools who would not have taken the GSAT.

[12] Monetary figures expressed in real 2019 U.S. dollars in purchasing power parity (PPP).

both girls and boys consistently rank more selective schools higher, the choices of girls are always relatively more selective than those of boys. About 40-45% were assigned to one of their first three school choices.

About 53% of boys took at least one CSEC subject compared to about 73% of girls. Similarly, while 27.4% of girls qualified for tertiary education based on CSEC performance (i.e., passing at least five subjects including English and math), only 14.9% of boys achieved the same. Post-secondary outcomes confirm this pattern; 16.9% of girls took the CAPE, against 9% of boys. CAPE success also favors girls, with 7% of them earning an Associate Degree, against 3.2% of boys.[13]

4 Empirical Strategy

4.1 The Impact of Preferred Secondary Schools

The centralized school assignment mechanism creates a test score cutoff above which applicants to each school are admitted and below which they are not. Since parents list their school choices before students sit the GSAT and the cutoffs are a function of the (unknown) national distributions of GSAT scores and school choices, cutoffs cannot be gamed. If nothing else differs among those scoring just above and just below the cutoff, any sudden change in outcomes as students' GSAT score goes from below to above the cutoff for a preferred school can be attributed to attending that preferred school (Hahn et al., 2001). Therefore, one can exploit the discontinuity in the likelihood of admission through the cutoff by estimating the following two-stage least-squares (2SLS) model:

$$Attend_{ijt} = \delta \cdot Above_{ijt} + g_1(GSAT_{ijt}) + \mathbf{X_{it}'}\boldsymbol{\omega_1} + C_{1,jt} + \varepsilon_{1,ijt} \tag{1}$$

$$Y_{ijt} = \theta \cdot \hat{Attend}_{ijt} + g_2(GSAT_{ijt}) + \mathbf{X_{it}'}\boldsymbol{\omega_2} + C_{2,jt} + \varepsilon_{2,ijt} \tag{2}$$

The first stage (1) predicts whether individual i who belongs to GSAT cohort t attended school j , $Attend_{ijt}$, as a function of scoring above the cutoff for preferred school j within GSAT cohort t, $Above_{ijt}$, and controls.[14] To account for latent outcomes that vary smoothly through the cutoffs, the model controls for a smooth function of the GSAT score (relative to each school cutoff j) fully interacted with the $Above_{ijt}$ indicator, $g_1(GSAT_{ijt})$. We also include all controls collected at PATH application (included in X_{it}).[15] Following Jackson (2010) and Pop-Eleches and Urquiola (2013), we stack the data across all schools' application pools into a single cutoff, recenter GSAT scores

[13]Our analyses focuses on PATH applicants. However, we possess the full population GSAT, CSEC and CAPE data. In Appendix Table A.2 we show how PATH applicants differ from non-applicants confirming that applicants constitute a relatively underprivileged segment of the population.

[14]We code the attended school as the one in which the student was enrolled in the last year (i.e., fifth year) of secondary studies. For those who leave school early, we use the MOEY administrative school assignment.

[15]These include parish of residency fixed effects, gender, education of the household member who filed the PATH application, household income, home ownership status, and household size, all measured at the time PATH application.

at each respective cutoff, and include cutoff fixed effects ($C_{1,jt}$). The cutoff fixed effects ensure that all comparisons are among students who applied to the same school in the same year.[16] In the second stage (2), the outcome of interest (Y_{ijt}) is a function of predicted preferred school attendance and all controls from Equation (1). The second stage excluded instrument is $Above_{ijt}$. Because the same individual can enter the stacked database for more than one cutoff, the estimated standard errors are clustered at the individual level.[17] In this context, estimates of yield the causal effect of attending a preferred secondary school on the outcome of interest.

4.2 Interactions between PATH and Preferred Secondary Schools

To estimate interaction effects between PATH and preferred secondary school attendance, we extend the model outlined in (1) – (2) by exploiting the fact that, at each school cutoff, we observe PATH applicants who were eligible and ineligible for PATH benefits as a result of their household's PMT score. Using the stacked database described above, we estimate the following 2SLS model:

$$\begin{aligned} Received_{it} = \pi_1 \cdot AboveP_{it} + \delta_1 \cdot Above_{ijt} + \varphi_1 \cdot AboveP_{it} \cdot Above_{ijt} + f_1(Score_{it}) + g_1(GSAT_{ijt}) \\ + f_1(Score_{it}) \cdot g_1(GSAT_{ijt}) + \mathbf{X'_{it}} \boldsymbol{\vartheta_1} + C_{1,jt} + \varepsilon_{1,ijt} \end{aligned} \tag{3}$$

$$\begin{aligned} Attend_{ijt} = \pi_2 \cdot AboveP_{it} + \delta_2 \cdot Above_{ijt} + \varphi_2 \cdot AboveP_{it} \cdot Above_{ijt} + f_2(Score_{it}) + g_2(GSAT_{ijt}) \\ + f_2(Score_{it}) \cdot g_2(GSAT_{ijt}) + \mathbf{X'_{it}} \boldsymbol{\vartheta_2} + C_{2,jt} + \varepsilon_{2,ijt} \end{aligned} \tag{4}$$

$$\begin{aligned} Received_{it} \cdot Attend_{ijt} = \pi_3 \cdot AboveP_{it} + \delta_3 \cdot Above_{ijt} + \varphi_3 \cdot AboveP_{it} \cdot Above_{ijt} + f_3(Score_{it}) \\ + g_3(GSAT_{ijt}) + f_3(Score_{it}) \cdot g_3(GSAT_{ijt}) + \mathbf{X'_{it}} \boldsymbol{\vartheta_3} + C_{3,jt} + \varepsilon_{3,ijt} \end{aligned} \tag{5}$$

$$\begin{aligned} Y_{ijt} = \beta_1 \cdot \widehat{Received}_{it} + \theta_1 \cdot \widehat{Attend}_{ijt} + \tau \cdot \widehat{Received_{it} \cdot Attend_{ijt}} + f_4(Score_{it}) + g_4(GSAT_{ijt}) \\ + f_4(Score_{it}) \cdot g_4(GSAT_{ijt}) + \mathbf{X'_{it}} \boldsymbol{\vartheta_4} + C_{4,jt} + \varepsilon_{4,ijt} \end{aligned} \tag{6}$$

This model possesses three first stages corresponding to both individual interventions (i.e., PATH and preferred school attendance) and their interaction denoted by equations (3) – (5) respectively. In equation (3) the model predicts whether individual i who belongs to GSAT cohort t received PATH benefits, $Received_{it}$, as a function of scoring above the PATH eligibility threshold, $AboveP_{it}$, and additional controls previously defined in Section 4.1.[18] To account for latent outcomes that vary smoothly through the PATH eligibility thresholds, the model controls for a

[16] An individual student appears in all the cutoffs associated with the schools to which she applied. As we observe school choices, we do not rely on any assumptions regarding the schools to which students applied.

[17] In our context, this approach is equivalent to heteroskedasticity-robust estimated standard errors allowing for off-diagonal non-zero terms in the variance-covariance matrix when the same individual enters the data for more than one cutoff. Kolesár and Rothe (2018) show this to be a more conservative approach than also clustering estimated standard errors at the level of the running variable, $GSAT_{ijt}$.

[18] We use the negative of the PATH PMT score and eligibility thresholds in all our specifications.

smooth function of the PATH PMT score net of the eligibility threshold fully interacted with the $AboveP_{it}$ indicator, $f_1(Score_{it})$. Equation (4) models preferred school attendance as a function of scoring above the school admission cutoff and all additional controls previously defined. Equation (5) models the interaction between PATH reception and preferred school attendance as a function of the interaction of the two excluded instruments ($AboveP_{it}$ and $Above_{ijt}$) and all other controls.[19]

The second stage (6) delivers the parameters of interest. Estimates of β_1 denote the effect of PATH for those who subsequently did not attend a preferred secondary school. Estimates of θ_1 denote the effect of having attended a preferred school for those who did not receive PATH. Estimates of τ capture the interaction between PATH and preferred school attendance. A positive coefficient would denote the additional return that PATH beneficiaries could expect from attending a preferred school with respect to non-beneficiaries. Conversely, a negative coefficient would represent the diminished return to attending a preferred school that PATH beneficiaries could expect with respect to non-beneficiaries. The combined effect of having received PATH benefits and subsequently having attended a preferred school with respect to the average individual who did not receive any intervention is given by $\beta_1 + \theta_1 + \tau$.

The key identifying assumptions in this combined discontinuity model are that nothing other than PATH reception changes discontinuously through the PATH eligibility threshold and also that nothing other than preferred school attendance changes discontinuously through the school admission cutoff. To show that these assumptions likely hold, we first show that PATH reception, preferred school attendance, and their interaction are strongly correlated with their own excluded instruments. Appendix Table A.3 (panel A) shows the estimates of π_1 from equation (3), δ_2 from equation (4), and φ_3 from equation (5). All first-stage estimates are highly significant for both boys and girls. The first stages for both PATH reception and preferred school attendance by gender are depicted in Figure 1. Second, we show that the baseline socioeconomic composition of households remains smooth through both the PATH eligibility threshold and the preferred school cutoffs. We follow Kling et al. (2007) and compute a baseline sociodemographic standardized index defined as the equally weighted average of the z-scores of all available sociodemographic variables reported at PATH application.[20] We then estimate reduced-form models as in equation (3) with the baseline sociodemographic index as dependent variable.[21] If our identification assumptions hold, we should not observe discernible relations between the excluded instruments and the sociodemographic index. That is, estimates of π_1, δ_1, and φ_1 should be statistically indistinguishable from

[19] For all main results, we exploit all available observations, and model both $f(Score_{it})$ and $g(GSAT_{ijt})$ with 3rd-order polynomials. However, as we show in Section 5.4, our results are robust to alternative polynomial orders and when computing optimal bandwidths according to Calonico et al. (2017).

[20] These include parish of residency, gender of the household head, education of the household head, household income, home ownership status, and household size.

[21] Here we do not control for baseline characteristics as these are included in the sociodemographic index.

zero. Appendix Table A.3 (panel B) displays these estimates which are small in magnitude and indistinguishable from zero, supporting that the exclusion restrictions likely hold. Third, we follow McCrary (2008) and test for a discontinuity in density through both the PATH eligibility threshold and the school admission cutoffs, finding no discontinuities (Appendix Table A.3, panel C).

Since our main objective is exploring whether returns to preferred school attendance vary by PATH participation, we also require that PATH beneficiaries and non-beneficiaries are comparable across the eligibility threshold. We assess this requirement through the estimation of the following 2SLS model:

$$Received_{it} = \lambda \cdot AboveP_{it} + f_1(Score_{it}) + \mathbf{X'_{it}}\vartheta_\mathbf{1} + C_{1,jt} + \varepsilon_{1,ijt} \tag{7}$$

$$O_{ijt} = \beta_2 \cdot \widehat{Received}_{it} + f_2(Score_{it}) + \mathbf{X'_{it}}\vartheta_\mathbf{2} + C_{2,jt} + \varepsilon_{2,ijt} \tag{8}$$

Our identification framework requires an orthogonal relation between PATH participation and characteristics that determine preferred school attendance (i.e., insignificant estimates of β_2). Appendix Table A.4 displays estimates of β_2. These are small and statistically indistinguishable from zero showing that PATH beneficiaries and non-beneficiaries are balanced in terms of GSAT performance, academic peer quality, selectivity of school choices, and school placements.[22] These tests suggest that our strategy is likely valid.[23]

5 Results and Discussion

5.1 Preferred Secondary Schools and Learning Environments

We begin by documenting the consequences of attending a preferred secondary school on the learning environments experienced by pupils. We estimate the 2SLS model (1)-(2) with available measures of the environments of attended schools as dependent variables. Appendix Table A.5 reports estimates of the θ parameter from equation (2) for both boys and girls.

Attending a preferred school increases peer GSAT quality by 0.54 (0.41) sd for boys (girls). This is roughly the difference in average school selectivity between the top and the fourth school choice. Preferred school attendance also leads to more academically homogeneous cohorts (as

[22] Focusing on a reduced sample of PATH applicants during the period 2007-08 within urban areas of 10 (out of 14) parishes, Stampini et al. (2018) finds that PATH increased GSAT performance of boys by 5.1%. In our case, when focusing on the full population of PATH applicants between 2001 and 2013, we find no discernible relation between PATH eligibility and GSAT performance. Consistent with Stampini et al. (2018), we also find no relation between PATH and educational aspirations as measured by the selectivity of school choices.

[23] Given our objective of assessing interaction effects between PATH and preferred secondary schools, our analyses focus on PATH applicants who took the GSAT (i.e., applied to secondary school). A separate question pertains to whether PATH had direct effects on school progression among all PATH applicants. Appendix B reports these estimates showing that PATH participation favored primary to secondary school progression by about 5 percentage points. However, it also shows that, conditional on taking the GSAT, PATH had no effects on learning.

evidenced by the reduced incoming GSAT score gap among admitted students to each school). More academically able peers within more homogeneous groups have been shown to favor learning (Duflo et al., 2011; Jackson, 2010; Pop-Eleches and Urquiola, 2013). Preferred schools appear to be more diverse, as evidenced by the reduced Herfindahl–Hirschman Index (HHI) computed using the shares of parishes of origin among students within each school.

Using the 2009 Teacher Census, we computed the proportion of teachers who hold a university degree within each school. Appendix Table A.5 shows that attending a preferred school increases the exposure of students to teachers with university degrees. We also extracted school-level information from the School Inspection Reports conducted by the National Education Inspectorate which covered 364 secondary schools between 2010 and 2015.[24] These reports provide information on pupil-teacher ratios and yearly average student attendance rates. They also deliver school ratings based on several dimensions of school management, as well as academic and nonacademic performance of students.[25] Attending a preferred school is significantly associated with lower pupil-teacher ratios, higher attendance rates, and improved overall school ratings.[26] These characteristics are also consistent with environments that favor learning outcomes (Glewwe et al., 2021).

5.2 Does PATH influence the Effectiveness of Preferred Secondary Schools?

We now focus on potential interactions between PATH and preferred school attendance on secondary and post-secondary academic outcomes. Table 2 (panel A) reports estimates of β_1, θ_1 and τ from equation (6) for boys and girls. We observe no discernible direct effects of PATH on learning outcomes for either boys or girls (i.e., estimates of β_1). The only exception is a positive effect on the likelihood of taking at least one CSEC subject among boys equivalent to 2.54 percentage points ($p-value$<0.05). This reflects a 4.75% increase with respect to the average CSEC taking rate of 53.4% among boys. While this outcome does not measure a learning effect, it serves as a proxy for secondary school completion and is consistent with previous evidence suggesting positive effects of CCTs on secondary graduation rates (Baez and Camacho, 2011; Araujo et al., 2017; Attanasio et al., 2021).

When looking at the direct effects of attending a preferred school (i.e., estimates of θ_1), we observe a different picture. In terms of taking the CSEC, no discernable effects are found among boys.

[24] These reports can be accessed at: https://www.nei.org.jm/Inspection-Findings/School-Reports

[25] These dimensions include: (1) leadership and management; (2) teaching in support of student learning; (3) students performance in English and math; (4) students personal and social development; (5) use of human and material resources; (6) curriculum and enhancement programs; and (7) provisions for safety, security, health and well-being. Each of these dimensions were rated on a scale ranging from 1 (extremely poor) to 5 (exceptionally high). The overall effectiveness rating is a composite of all the measured dimensions which also ranges between 1 and 5. We, therefore, compute a normalized effectiveness index for each school j which ranges between 0 and 1 as follows: ($EffectivenessRating_j$ - 1)/(5 - 1).

[26] Appendix Table A.6 reports preferred school effects on each individually rated dimension evidencing positive impacts on all of them.

However, we observe a negative effect of 3.53 percentage points among girls ($p-value$<0.01). While this effect is modest relative to the average CSEC taking rate of 72.8% among girls, it might suggest that more selective schools either increase dropout among girls or discourage marginal students from taking the CSEC to avoid potential worsening of the school average CSEC performance.[27] However, preferred school attendance conveys significant benefits on individual-level CSEC performance. Both boys and girls experience an increase of 8–9 percentage points ($p-value$<0.01) in the likelihood of qualifying for tertiary education based on CSEC performance (i.e., passing at least five CSEC subjects, including English and math). The magnitudes of these effects are relatively large with respect to the average CSEC passing rate of 14.9% for boys and 27.4% for girls. Post-secondary CAPE outcomes are also positively affected for both boys and girls. The likelihood of taking the CAPE increases by 5.3 (8.4) percentage points among boys (girls); while the likelihood of earning an Associate Degree goes up by 5.4 (9) percentage points among boys (girls). These effects are substantial with respect to the average CAPE taking rates of 9.1% (16.7%) among boys (girls), and the proportion of boys (girls) with an Associate Degree of 3.2% (7%).

We now explore whether the effectiveness of preferred schools differ between comparable PATH recipients and non-recipients. This is captured by the estimates of the τ parameter presented in Table 2 (panel A). These estimates capture the differential benefits that PATH recipients experienced from attending a preferred school with respect to those experienced by comparable non-recipients. Our estimates suggest negative and significant interactions among boys but no discernible interactions among girls.

Regarding the likelihood of qualifying for tertiary education based on CSEC performance among boys, the estimate is -3.13 percentage points ($p-value$<0.01). This implies that the previously found benefit of attending a preferred school equivalent to 8.23 percentage points on this outcome among boys who did not receive PATH benefits, is diminished by 3.13 percentage points for PATH recipients. To portray this finding, Table 2 (panel B) computes the total effect of having received PATH benefits and subsequently attended a preferred school (i.e., $\beta_1 + \theta_1 + \tau$). Among boys, the combined effect is 5.43 percentage points ($p-value$<0.01). While this combined effect is positive, it is significantly lower than the 8.23 percentage points effect enjoyed by boys who did not receive PATH benefits and subsequently attended a preferred school. Similar findings are observed for CAPE outcomes among boys.

Overall, we document that: (a) for both boys and girls who did not attend a preferred secondary school, PATH reception had no direct effects on learning; (b) for girls who attended a preferred school, the returns to preferred school attendance were unaltered by PATH reception; and (c) for

[27] Jackson (2010) also finds negative effects of school selectivity on the likelihood of taking the CSEC when using a similar discontinuity model in Trinidad and Tobago.

boys who attended a preferred school, the returns to preferred school attendance were significantly lower among PATH recipients with respect to comparable counterparts who did not receive PATH benefits.

5.3 Potential Mechanisms

Our main outcomes were measured without limiting the time window for CSEC/CAPE taking. As we have many rounds of data, we treated similarly those who obtained CSEC/CAPE certifications on time (i.e., within 5 years of GSAT taking for CSEC and within 7 years of GSAT taking for CAPE) and those who achieved so with delay. Since PATH requires a minimum school attendance rate of 85%, the program may have affected on time taking which could lead us to different conclusions. Appendix Table A.7 reports effects on CSEC and CAPE certifications achieved on time. Estimates are very similar to our main results, suggesting that this possibility is not driving our findings.

The categorical outcomes that we measure may mask potentially different effects at the intensive margin. It might be that school effectiveness by PATH status could be different when looking at the number of subjects taken. As PATH requires school attendance but enforcement of academic effort is not possible, students might reduce academic effort on the core (and more demanding) subjects and take other subjects that could be perceived as more useful for their lives. Since taking the core subjects is mandatory, such potential dynamic would lead PATH recipients to take relatively more subjects without achieving certifications (which requires passing the core subjects). Appendix Table A.8 reports estimates for the number of CSEC and CAPE subjects taken and passed; while Appendix Table A.9 does so for the number of CSEC an CAPE subjects taken and passed on time. These results mimic our main findings, suggesting that this potential mechanism is not driving our main conclusions.

Our evidence points out to within school dynamics that reduce their academic effectiveness among boys who are PATH beneficiaries. One possibility might be the stigmatization of PATH beneficiaries within preferred schools such that potential socio-emotional harm partly undoes the academic benefits of preferred school attendance. PATH beneficiaries are entitled to free meals and, therefore, this could reveal their beneficiary status to other students. This, coupled with evidence that bullying is more prevalent among boys with respect to girls (Currie et al., 2008; Sarzosa and Urzúa, 2021; Sarzosa, 2021), suggests this as a possible mechanism worth exploring in future research.

Due to data availability, we focus on school examinations and post-secondary certifications. While these outcomes are highly relevant, a complete picture would also need to assess the effects on a wider set of academic and nonacademic longer run outcomes. Existing evidence shows that school effects on test scores could differ from effects on other important outcomes like crime, teen pregnancy, and adult employment (Deming, 2011; Beuermann et al., 2021; Beuermann and Jackson, 2022). Therefore, the documented negative interactions between PATH and preferred school attendance on academic outcomes may not necessarily translate into similar results on other important longer-run outcomes.

5.4 Robustness

To assuage concerns that our results are driven by modelling choices, we show that our estimated effects are similar when computing optimal bandwidths according to Calonico et al. (2017) and to alternative polynomial specifications of the running variables (Appendix Tables A.10 - A.11).

6 Conclusions and Policy Implications

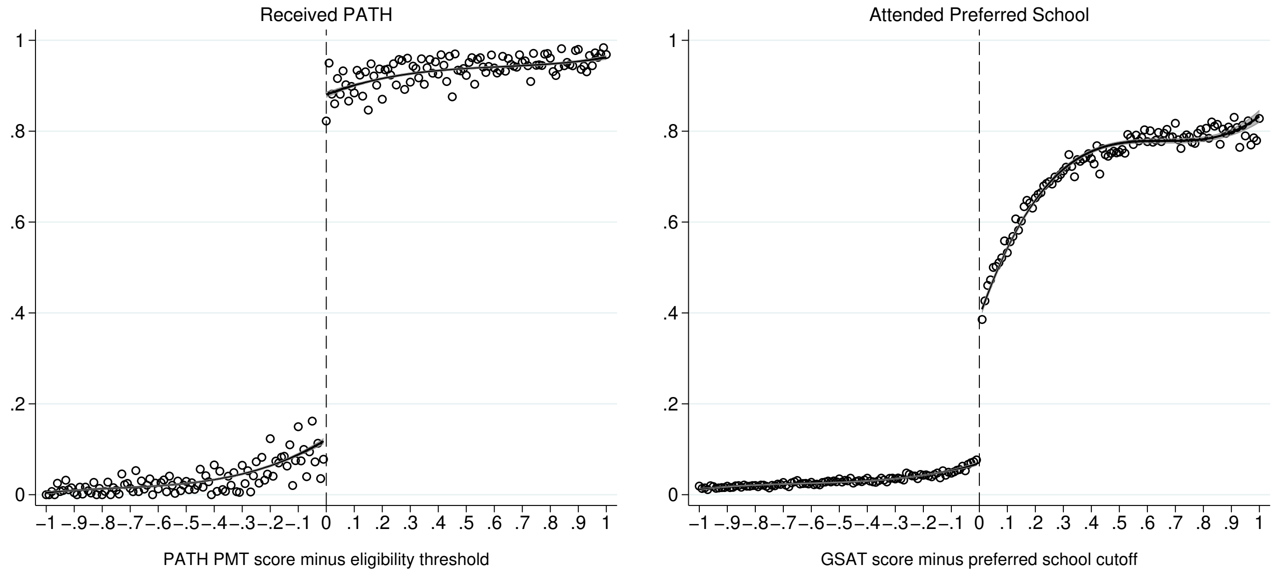
Potential interactions between different human capital interventions are highly relevant for policy design as different policies are not implemented in isolation and, therefore, the effectiveness of one policy could be affected by another. In this paper we exploit two sources of exogenous variation determining eligibility into two human capital development interventions. These are the Programme of Advancement through Health and Education (Jamaica's Conditional Cash Transfer Program or PATH) and the subsequent attendance to a preferred (or more selective) secondary school.

Administrative data covering the full population of students delivers three main results. First, for both boys and girls, benefiting from PATH had no direct effects on secondary and post-secondary learning. Second, for girls who attended a preferred secondary school, the returns to preferred school attendance were unaltered by PATH participation. Third, for boys who attended a preferred secondary school, the returns to preferred school attendance were significantly lower among PATH beneficiaries when compared to equivalent counterparts who did not receive PATH. This implies that, among boys, PATH reception is partly undoing the potential benefits to attending a more selective secondary school.

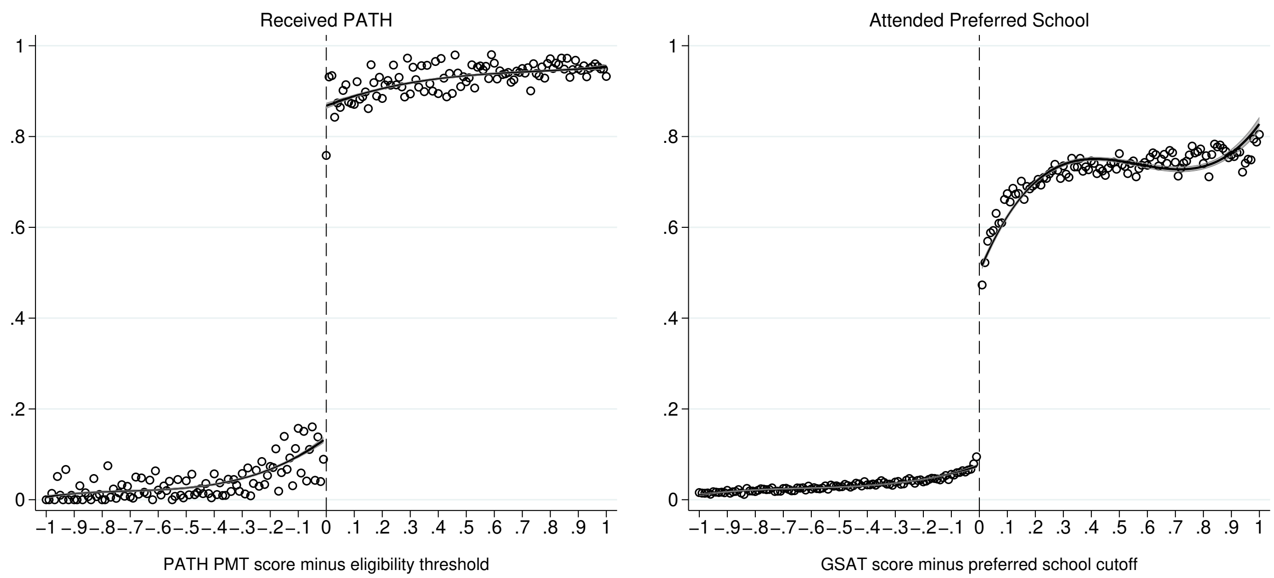
Overall, our evidence highlights the importance of understanding and measuring potential interaction effects between different public interventions. As Conditional Cash Transfers have proliferated across many nations, our findings portray the need to evaluate whether these programs are also altering the effectiveness of other human capital development interventions. The existence of potential interactions across programs convey important implications for cost-benefit analyses of individual programs and our findings suggest that this might be a relevant issue.

Figure 1: First Stage

Panel A: Boys



Panel B: Girls



Notes: Left panels: The Y-axis represents the likelihood of having received PATH benefits. The X-axis is the (minus) PATH PMT standardized score relative to the eligibility threshold. The circles are means corresponding to 0.25-point bins of the standardized relative score. The solid lines are generated by fitting a third degree polynomial of the relative score fully interacted with the 'AboveP' indicator. Right panels: The Y-axis represents the likelihood of having attended a preferred school. The X-axis is the GSAT standardized score relative to the preferred school admission cutoff. The circles are means corresponding to 0.25-point bins of the standardized relative score. The solid lines are generated by fitting a third degree polynomial of the relative score fully interacted with the 'Above' indicator. All panels: The 95 percent confidence interval of the fitted polynomials are presented in light gray.

Table 1: Summary Statistics

	Boys			Girls		
	mean	sd	N	mean	sd	N
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline indicators at PATH application (PATH applicants 2001 - 2013)						
Age at PATH application (in months)	80.4292	26.5825	106,952	79.8970	26.9368	113,140
PATH applicant is female	0.8580	0.3491	106,952	0.8633	0.3435	113,140
PATH applicant completed secondary education	0.3831	0.4861	106,952	0.3788	0.4851	113,140
Household income per week - real 2019 PPP US$	25.7866	20.0508	106,952	25.6181	18.6474	113,140
Own dwelling	0.4251	0.4944	106,952	0.4220	0.4939	113,140
Household size	5.7471	2.7176	106,952	5.7674	2.7307	113,140
Received PATH	0.4946	0.5000	106,952	0.5025	0.5000	113,140
Panel B: Academic indicators						
Age at GSAT date (in months)	143.7216	5.4064	106,952	142.8496	5.2366	113,140
GSAT standardized score	-0.2374	1.0060	106,952	0.2245	0.9406	113,140
Peer GSAT score	-0.1259	0.8432	106,952	0.1456	0.8441	113,140
Selectivity of school choice 1	1.1373	0.7605	106,506	1.3898	0.6463	112,837
Selectivity of school choice 2	0.9547	0.7719	106,452	1.2118	0.6850	112,802
Selectivity of school choice 3	0.7885	0.8094	106,340	1.0697	0.7477	112,711
Selectivity of school choices 4+	0.5586	0.7135	99,160	0.7667	0.6971	104,884
Assigned to school choice 1	0.1595	0.3662	106,952	0.1496	0.3566	113,140
Assigned to school choice 2	0.1401	0.3471	106,952	0.1316	0.3380	113,140
Assigned to school choice 3	0.1418	0.3488	106,952	0.1213	0.3264	113,140
Assigned to school choice 4+	0.5586	0.4966	106,952	0.5976	0.4904	113,140
Took CSEC	0.5344	0.4988	106,952	0.7283	0.4449	113,140
CSEC qualification for tertiary education	0.1490	0.3561	106,952	0.2736	0.4458	113,140
Took CAPE	0.0907	0.2872	96,171	0.1686	0.3744	100,975
Associate Degree	0.0316	0.1748	96,171	0.0700	0.2552	100,975

Notes: This table displays means (columns 1 and 4), standard deviations (columns 2 and 5), and number of individual observations (columns 3 and 6) differentiated by gender. For CSEC outcomes, we use GSAT cohorts up to 2015 because CSEC is taken five years after GSAT and the latest CSEC data available is for year 2020. The number of observations for CAPE outcomes are lower as these are restricted up to GSAT cohort 2013 given that the CAPE is fully taken seven years after GSAT and the latest CAPE data available is for 2020.

Table 2: Interactions between PATH and Preferred School Attendance

	Boys				Girls			
	Took CSEC	CSEC qualification for tertiary education	Took CAPE	CAPE Associate Degree	Took CSEC	CSEC qualification for tertiary education	Took CAPE	CAPE Associate Degree
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS Parameter Estimates								
Received PATH (β_1)	0.0254**	0.0033	-0.0005	-0.0001	-0.0118	0.0025	0.0014	0.0075
	(0.0111)	(0.0066)	(0.0054)	(0.0030)	(0.0103)	(0.0089)	(0.0075)	(0.0047)
Attended preferred school (θ_1)	-0.0057	0.0823***	0.0529***	0.0540***	-0.0353***	0.0892***	0.0841***	0.0900***
	(0.0106)	(0.0098)	(0.0094)	(0.0068)	(0.0077)	(0.0086)	(0.0088)	(0.0064)
Received PATH x Attended preferred school (τ)	-0.0083	-0.0313***	-0.0123*	-0.0110***	-0.0056	-0.0128	-0.0030	-0.0006
	(0.0098)	(0.0073)	(0.0065)	(0.0041)	(0.0089)	(0.0088)	(0.0084)	(0.0061)
Panel B: PATH plus preferred school attendance								
Combined effect ($\beta_1 + \theta_1 + \tau$)	0.0114	0.0543***	0.0401***	0.0428***	-0.0526***	0.0788***	0.0825***	0.0970***
	(0.0147)	(0.0118)	(0.0107)	(0.0074)	(0.0125)	(0.0126)	(0.0118)	(0.0081)
p-value: ($\theta_1 = \beta_1 + \theta_1 + \tau$)	0.16	<0.01	0.10	0.02	0.11	0.35	0.88	0.33
Observations	317,901	317,901	285,474	285,474	346,136	346,136	307,522	307,522

Notes: Panel A displays estimated 2SLS coefficients on 'Received' PATH benefits (1), on 'Attend' a preferred secondary school (1), and on their interaction () resulting from equation system (3) - (6) in the text. Panel B displays the addition of the estimated parameters reported in Panel A. Panel B also shows the p-value of the null of equality between the direct school effect and the combined effect adding PATH, school effect, and their interaction. Estimated standard errors clustered at the individual level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

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7 Appendix A: Supplemental Tables

Table A.1: Sample Composition by Year of Birth and PATH Application Year

Year of	Year of PATH Application													Total
Birth	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	
1991	1,562	0	0	0	0	0	0	0	0	0	0	0	0	1,562
1992	1,514	16,272	0	0	0	0	0	0	0	0	0	0	0	17,786
1993	1,653	18,123	2,127	0	0	0	0	0	0	0	0	0	0	21,903
1994	1,780	19,183	2,002	807	0	0	0	0	0	0	0	0	0	23,772
1995	1,927	18,834	1,988	755	901	0	0	0	0	0	0	0	0	24,405
1996	1,830	17,833	1,751	729	804	1,524	0	0	0	0	0	0	0	24,471
1997	1,729	16,562	1,714	723	856	1,450	1,060	0	0	0	0	0	0	24,094
1998	1,505	14,945	1,500	621	734	1,332	976	1,834	0	0	0	0	0	23,447
1999	0	13,579	1,386	599	700	1,325	985	1,775	924	0	0	0	0	21,273
2000	0	0	1,373	601	748	1,424	1,094	2,024	939	891	0	0	0	9,094
2001	0	0	0	535	677	1,318	1,101	1,927	904	848	726	0	0	8,036
2002	0	0	0	0	1,166	2,194	1,454	2,820	1,339	1,163	931	674	0	11,741
2003	0	0	0	0	0	1,844	1,146	2,038	1,002	971	704	500	303	8,508
Total	13,500	135,331	13,841	5,370	6,586	12,411	7,816	12,418	5,108	3,873	2,361	1,174	303	220,092

Notes: Sample includes all households who applied for PATH benefits between 2001 and 2013, with at least one member within the age range of 3 to 10 years old, and within years of birth that allow sufficient time to reach the age of GSAT taking between 2003 and 2015.

Table A.2: Differences in Academic Indicators between PATH Applicants and Non-Applicants

	Boys							Girls						
	Non-Applicants			Applicants			p-value	Non-Applicants			Applicants			p-value
	Mean (1)	SD (2)	N (3)	Mean (4)	SD (5)	N (6)	(1)=(4) (7)	Mean (8)	SD (9)	N (10)	Mean (11)	SD (12)	N (13)	(8)=(11) (14)
Age at GSAT date (in months)	142.6544	5.6120	110,695	143.7216	5.4064	106,952	<0.01	141.6989	5.4749	110,235	142.8496	5.2366	113,140	<0.01
GSAT standardized score	0.4201	1.1510	110,695	-0.2374	1.0060	106,952	<0.01	0.7816	1.0044	110,235	0.2245	0.9406	113,140	<0.01
Peer GSAT score	0.4429	0.9931	110,695	-0.1259	0.8432	106,952	<0.01	0.6962	0.9519	110,235	0.1456	0.8441	113,140	<0.01
Selectivity of school choice 1	1.5526	0.6073	110,662	1.1373	0.7605	106,506	<0.01	1.7266	0.4848	110,208	1.3898	0.6463	112,837	<0.01
Selectivity of school choice 2	1.3719	0.7012	110,633	0.9547	0.7719	106,452	<0.01	1.5602	0.5813	110,188	1.2118	0.6850	112,802	<0.01
Selectivity of school choice 3	1.2137	0.7605	110,259	0.7885	0.8094	106,340	<0.01	1.4410	0.6435	109,972	1.0697	0.7477	112,711	<0.01
Selectivity of school choices 4+	0.9663	0.7183	92,381	0.5586	0.7135	99,160	<0.01	1.1625	0.6570	92,815	0.7667	0.6971	104,884	<0.01
Assigned to school choice 1	0.1845	0.3879	110,695	0.1595	0.3662	106,952	<0.01	0.1915	0.3935	110,235	0.1496	0.3566	113,140	<0.01
Assigned to school choice 2	0.1375	0.3444	110,695	0.1401	0.3471	106,952	0.08	0.1328	0.3394	110,235	0.1316	0.3380	113,140	0.39
Assigned to school choice 3	0.1330	0.3396	110,695	0.1418	0.3488	106,952	<0.01	0.1016	0.3021	110,235	0.1213	0.3264	113,140	<0.01
Assigned to school choice 4+	0.5450	0.4980	110,695	0.5586	0.4966	106,952	<0.01	0.5741	0.4945	110,235	0.5976	0.4904	113,140	<0.01
Took CSEC	0.6153	0.4865	110,695	0.5344	0.4988	106,952	<0.01	0.7345	0.4416	110,235	0.7283	0.4449	113,140	<0.01
CSEC qualification for tertiary education	0.2869	0.4523	110,695	0.1490	0.3561	106,952	<0.01	0.4161	0.4929	110,235	0.2736	0.4458	113,140	<0.01
Took CAPE	0.1891	0.3916	95,630	0.0907	0.2872	96,171	<0.01	0.2921	0.4547	94,563	0.1686	0.3744	100,975	<0.01
CAPE Associate Degree	0.0836	0.2768	95,630	0.0316	0.1748	96,171	<0.01	0.1511	0.3582	94,563	0.0700	0.2552	100,975	<0.01

Notes: This table presents summary statistics of academic indicators extracted from the full population matched data across the GSAT, CSEC and CAPE registries. The ”Applicants” sample refers to individuals who applied to the PATH program and were subsequently observed in the GSAT registries (i.e., the PATH-GSAT matched sample analyzed in this study.). The ”Non-Applicants” sample refers to individuals who are observed in the GSAT registries but did not apply to the PATH program. Column (7) displays the *p-value* of a test for the null of equality of means shown in columns (1) and (4). Column (14) displays the *p-value* of a test for the null of equality of means shown in columns (8) and (11).

Table A.3: Validity of the Identification Strategy

	Boys	Girls
	(1)	(2)
Panel A: First Stage		
AboveP ($_1$)	0.7991***	0.7752***
	(0.0054)	(0.0055)
Above ($_2$)	0.3111***	0.4313***
	(0.0055)	(0.0049)
AboveP x Above ($_3$)	0.5151***	0.5011***
	(0.0036)	(0.0036)
Panel B: Exclusion restriction (sociodemographic index)		
AboveP ($_1$)	0.0008	0.0037
	(0.0024)	(0.0022)
Above ($_1$)	-0.0002	0.0009
	(0.0015)	(0.0014)
AboveP x Above ($_1$)	-0.0019	-0.0003
	(0.0014)	(0.0014)
Panel C: Differential density		
PATH eligibility threshold	0.2890	0.1703
[p-value]	[0.7726]	[0.8648]
Preferred school admission cutoff	-0.4794	-0.2301
[p-value]	[0.6317]	[0.8180]
Observations	317,901	346,136

Notes: Panel A reports first stage estimated coefficients on 'AboveP' from equation (3); first stage estimated coefficients on 'Above' from equation (4); and first stage estimated coefficients on 'AboveP' x 'Above' from equation (5). Panel B displays estimated coefficients on the 'AboveP', 'Above', and 'AboveP' x 'Above' having the baseline sociodemographic index as dependent variable within a reduced-form model with the same structure as equation (3). Panel C reports the results of the McCrary (2008) cutoff manipulation test around both the PATH eligibility cutoff and the preferred school admission cutoff. Estimated standard errors clustered at the individual level are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.4: PATH 2SLS effects on GSAT Outcomes

	Boys		Girls	
	Effects	N	Effects	N
	(1)	(2)	(3)	(4)
GSAT standardized score	0.0097	317,901	0.0075	346,136
	(0.0110)		(0.0103)	
Peer GSAT score	0.0073	317,901	0.0150	346,136
	(0.0102)		(0.0100)	
Selectivity of school choice 1	0.0028	317,829	0.0005	346,042
	(0.0019)		(0.0017)	
Selectivity of school choice 2	-0.0002	317,825	-0.0010	346,019
	(0.0018)		(0.0017)	
Selectivity of school choice 3	0.0001	317,627	-0.0007	345,855
	(0.0020)		(0.0019)	
Selectivity of school choice 4+	-0.0016	303,210	0.0004	330,601
	(0.0018)		(0.0018)	
Assigned to school choice 1	0.0027	317,901	0.0000	346,136
	(0.0020)		(0.0019)	
Assigned to school choice 2	0.0016	317,901	0.0002	346,136
	(0.0034)		(0.0031)	
Assigned to school choice 3	0.0021	317,901	0.0029	346,136
	(0.0048)		(0.0042)	
Assigned to school choice 4+	-0.0064	317,901	-0.0031	346,136
	(0.0060)		(0.0054)	

Notes: This table displays 2SLS estimated coefficients on 'Received' PATH benefits using 'AboveP' as the excluded instrument (resulting from equation system (7) - (8) in the text). Estimated standard errors clustered at the individual level are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.5: Preferred School 2SLS Effects on Learning Environments

	Boys		Girls	
	Effects	N	Effects	N
	(1)	(2)	(3)	(4)
Peer GSAT score	0.5388***	317,901	0.4075***	346,136
	(0.0150)		(0.0109)	
GSAT score gap (best-worst)	-0.0892***	317,901	-0.2933***	346,136
	(0.0343)		(0.0224)	
Parish HHI of attended school	-0.0590***	317,901	-0.0508***	346,136
	(0.0059)		(0.0044)	
Teachers with a university degree (%)	1.5673***	305,897	3.4558***	329,903
	(0.3267)		(0.2148)	
Pupil-Teacher Ratio	-0.7413***	298,932	-0.5793***	320,584
	(0.1376)		(0.0842)	
Attendance Rate (%)	3.7731***	290,345	3.5648***	310,122
	(0.2673)		(0.1671)	
Overall Effectiveness Index	0.1032***	300,458	0.1465***	321,911
	(0.0067)		(0.0047)	

Notes: This table displays 2SLS estimated coefficients on 'Attend' a preferred secondary school using 'Above' as the excluded instrument (resulting from equation system (1) - (2) in the text). The proportion of teachers with university degree was computed for each school measured in the 2009 Teacher Census. Estimated standard errors clustered at the individual level are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.6: Preferred Schools 2SLS Effects on Schools' Effectiveness Dimensions

	Boys		Girls	
	Effects (1)	N (2)	Effects (3)	N (4)
Overall Effectiveness - index	0.1032*** (0.0067)	300,458	0.1465*** (0.0047)	321,911
Overall Effectiveness - exceptionally high or good	0.2466*** (0.0115)	300,458	0.3172*** (0.0092)	321,911
Leadership and Management - index	0.0775*** (0.0073)	300,458	0.0997*** (0.0051)	321,911
Leadership and Management - exceptionally high or good	0.1926*** (0.0142)	300,458	0.2292*** (0.0109)	321,911
Teaching in Support of Students learning - index	0.0941*** (0.0060)	300,458	0.1239*** (0.0042)	321,911
Teaching in Support of Students learning - exceptionally high or good	0.2147*** (0.0104)	300,458	0.2371*** (0.0083)	321,911
Students Performance in English and Math - index	0.1621*** (0.0072)	300,346	0.2312*** (0.0056)	321,709
Students Performance in English and Math - exceptionally high or good	0.2508*** (0.0091)	300,458	0.3458*** (0.0085)	321,911
Students Progress in English and Math - index	0.0600*** (0.0061)	300,458	0.1242*** (0.0048)	321,911
Students Progress in English and Math - exceptionally high or good	0.0552*** (0.0061)	300,458	0.2096*** (0.0079)	321,911
Students Personal and Social Development - index	0.0774*** (0.0061)	300,458	0.1021*** (0.0043)	321,911
Students Personal and Social Development - exceptionally high or good	0.2673*** (0.0140)	300,458	0.3054*** (0.0109)	321,911
Use of Human and Material Resources - index	0.0392*** (0.0059)	300,458	0.0602*** (0.0041)	321,911
Use of Human and Material Resources - exceptionally high or good	0.1467*** (0.0119)	300,458	0.1626*** (0.0096)	321,911
Curriculum and enhancement programs - index	0.0971*** (0.0068)	300,458	0.0978*** (0.0047)	321,911
Curriculum and enhancement programs - exceptionally high or good	0.2477*** (0.0164)	300,458	0.2196*** (0.0120)	321,911
Provisions for safety, security, health and well-being - index	0.0328*** (0.0065)	300,458	0.0506*** (0.0045)	321,911
Provisions for safety, security, health and well-being - exceptionally high or good	0.0863*** (0.0171)	300,458	0.0970*** (0.0122)	321,911

Notes: This table displays 2SLS estimated coefficients on 'Attend' a preferred secondary school using 'Above' as the excluded instrument (resulting from equation system (1) - (2) in the text). Estimated standard errors clustered at the individual level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.7: Interactions between PATH and Preferred School Attendance - Outcomes measured after 5-7 years of GSAT taking

	Boys				Girls			
	Took CSEC within 5 years	CSEC qualification for tertiary education within 5 years	Took CAPE within 7 years	CAPE Associate Degree within 7 years	Took CSEC within 5 years	CSEC qualification for tertiary education within 5 years	Took CAPE within 7 years	CAPE Associate Degree within 7 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS Parameter Estimates								
Received PATH (β_1)	0.0085	0.0098*	0.0000	0.0018	-0.0085	-0.0023	0.0016	0.0079*
	(0.0104)	(0.0051)	(0.0052)	(0.0028)	(0.0108)	(0.0072)	(0.0074)	(0.0044)
Attended preferred school (θ_1)	-0.0231**	0.1255***	0.0552***	0.0590***	-0.0658***	0.1566***	0.0844***	0.0924***
	(0.0108)	(0.0084)	(0.0093)	(0.0065)	(0.0084)	(0.0080)	(0.0087)	(0.0062)
Received PATH x Attended preferred school (τ)	-0.0034	-0.0344***	-0.0147**	-0.0130***	-0.0024	-0.0148*	0.0002	-0.0014
	(0.0094)	(0.0063)	(0.0064)	(0.0039)	(0.0095)	(0.0079)	(0.0083)	(0.0059)
Panel B: PATH plus preferred school attendance								
Combined effect ($\beta_1+\theta_1+\tau$)	-0.0180	0.1010***	0.0404***	0.0478***	-0.0767***	0.1394***	0.0861***	0.0989***
	(0.0146)	(0.0099)	(0.0105)	(0.0071)	(0.0134)	(0.0111)	(0.0116)	(0.0078)
p-value: ($\theta_1=\beta_1+\theta_1+\tau$)	0.67	$<$0.01	0.06	0.02	0.36	0.08	0.86	0.35
Observations	317,901	317,901	285,474	285,474	346,136	346,136	307,522	307,522

Notes: Panel A displays estimated 2SLS coefficients on 'Received' PATH benefits (1), on 'Attend' a preferred secondary school (1), and on their interaction () resulting from equation system (3) - (6) in the text. Panel B displays the addition of the estimated parameters reported in Panel A. Panel B also shows the p-value of the null of equality between the direct school effect and the combined effect adding PATH, school effect, and their interaction. Estimated standard errors clustered at the individual level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.8: Interactions between PATH and Preferred School Attendance - Alternative Outcomes

	Boys				Girls			
	CSEC subjects taken	CSEC subjects passed	CAPE units taken	CAPE units passed	CSEC subjects taken	CSEC subjects passed	CAPE units taken	CAPE units passed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS Parameter Estimates								
Received PATH (β_1)	0.0888	0.0667	-0.0227	-0.0143	-0.0851	-0.0501	0.0149	0.0237
	(0.0624)	(0.0491)	(0.0317)	(0.0289)	(0.0720)	(0.0615)	(0.0454)	(0.0419)
Attended preferred school (θ_1)	0.1406**	0.1818***	0.4784***	0.4704***	-0.0973	0.0913*	0.7648***	0.7939***
	(0.0703)	(0.0625)	(0.0640)	(0.0606)	(0.0599)	(0.0549)	(0.0578)	(0.0546)
Received PATH x Attended preferred school (τ)	-0.1478**	-0.1529***	-0.0937**	-0.0844**	-0.0319	-0.0485	-0.0320	-0.0371
	(0.0590)	(0.0499)	(0.0410)	(0.0375)	(0.0648)	(0.0574)	(0.0548)	(0.0519)
Panel B: PATH plus preferred school attendance								
Combined effect ($\beta_1 + \theta_1 + \tau$)	0.0817	0.0956	0.3620***	0.3717***	-0.2144**	-0.0073	0.7477***	0.7805***
	(0.0917)	(0.0784)	(0.0708)	(0.0667)	(0.0927)	(0.0826)	(0.0749)	(0.0704)
p-value: ($\theta_1 = \beta_1 + \theta_1 + \tau$)	0.43	0.17	0.02	0.03	0.15	0.18	0.79	0.83
Observations	317,901	317,901	285,474	285,474	346,136	346,136	307,522	307,522

Notes: Panel A displays estimated 2SLS coefficients on 'Received' PATH benefits (1), on 'Attend' a preferred secondary school (1), and on their interaction () resulting from equation system (3) - (6) in the text. Panel B displays the addition of the estimated parameters reported in Panel A. Panel B also shows the p-value of the null of equality between the direct school effect and the combined effect adding PATH, school effect, and their interaction. Estimated standard errors clustered at the individual level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.9: Interactions between PATH and Preferred School Attendance - Alternative Outcomes measured after 5-7 years of GSAT taking

	Boys				Girls			
	CSEC subjects taken within 5 years	CSEC subjects passed within 5 years	CAPE units taken within 7 years	CAPE units passed within 7 years	CSEC subjects taken within 5 years	CSEC subjects passed within 5 years	CAPE units taken within 7 years	CAPE units passed within 7 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS Parameter Estimates								
Received PATH (β_1)	0.0557	0.0670	-0.0097	-0.0032	-0.0432	-0.0378	0.0231	0.0282
	(0.0519)	(0.0413)	(0.0293)	(0.0269)	(0.0658)	(0.0558)	(0.0430)	(0.0399)
Attended preferred school (θ_1)	0.2772***	0.3689***	0.5139***	0.5019***	-0.0144	0.2534***	0.7770***	0.8062***
	(0.0649)	(0.0582)	(0.0617)	(0.0587)	(0.0582)	(0.0533)	(0.0562)	(0.0533)
Received PATH x Attended preferred school (τ)	-0.1516***	-0.1800***	-0.1102***	-0.0981***	-0.0342	-0.0347	-0.0221	-0.0266
	(0.0518)	(0.0448)	(0.0388)	(0.0357)	(0.0617)	(0.0547)	(0.0533)	(0.0505)
Panel B: PATH plus preferred school attendance								
Combined effect ($\beta_1+\theta_1+\tau$)	0.1813**	0.2559***	0.3940***	0.4006***	-0.0917	0.1809**	0.7780***	0.8078***
	(0.0818)	(0.0707)	(0.0679)	(0.0644)	(0.0876)	(0.0781)	(0.0722)	(0.0681)
p-value: ($\theta_1=\beta_1+\theta_1+\tau$)	0.14	0.04	<0.01	0.02	0.32	0.30	0.99	0.98
Observations	317,901	317,901	285,474	285,474	346,136	346,136	307,522	307,522

Notes: Panel A displays estimated 2SLS coefficients on 'Received' PATH benefits (1), on 'Attend' a preferred secondary school (1), and on their interaction () resulting from equation system (3) - (6) in the text. Panel B displays the addition of the estimated parameters reported in Panel A. Panel B also shows the p-value of the null of equality between the direct school effect and the combined effect adding PATH, school effect, and their interaction. Estimated standard errors clustered at the individual level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.10: Interactions between PATH and Preferred School Attendance - Optimal Bandwidths and Linear Specification of Running Variables

	Boys				Girls			
	Took CSEC	CSEC qualification for tertiary education	Took CAPE	CAPE Associate Degree	Took CSEC	CSEC qualification for tertiary education	Took CAPE	CAPE Associate Degree
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS Parameter Estimates								
Received PATH (β_1)	0.0202**	0.0039	0.0080	0.0053*	0.0052	0.0122	0.0046	0.0026
	(0.0096)	(0.0078)	(0.0059)	(0.0027)	(0.0081)	(0.0096)	(0.0090)	(0.0060)
Attended preferred school (θ_1)	0.0402**	0.1147***	0.0822***	0.0474***	-0.0229**	0.0838***	0.0939***	0.0891***
	(0.0175)	(0.0109)	(0.0089)	(0.0046)	(0.0115)	(0.0122)	(0.0112)	(0.0074)
Received PATH x Attended preferred school (τ)	-0.0296	-0.0323**	-0.035***	-0.0183***	0.0176	-0.0128	0.0077	0.0018
	(0.0208)	(0.0143)	(0.0106)	(0.0050)	(0.0161)	(0.0178)	(0.0161)	(0.0101)
Panel B: PATH plus preferred school attendance								
Combined effect ($\beta_1+\theta_1+\tau$)	0.0309	0.0863***	0.0554***	0.0343***	-0.0001	0.0832***	0.1063***	0.0935***
	(0.0191)	(0.0108)	(0.0083)	(0.0042)	(0.0135)	(0.0133)	(0.0119)	(0.0077)
p-value: ($\theta_1=\beta_1+\theta_1+\tau$)	0.57	0.02	$<$0.01	$<$0.01	0.08	0.97	0.34	0.59
Observations	67,661	60,147	61,860	88,166	68,686	65,692	58,013	64,004

Notes: Panel A displays estimated 2SLS coefficients on 'Received' PATH benefits (1), on 'Attend' a preferred secondary school (1), and on their interaction () resulting from equation system (3) - (6) in the text. Panel B displays the addition of the estimated parameters reported in Panel A. Panel B also shows the p-value of the null of equality between the direct school effect and the combined effect adding PATH, school effect, and their interaction. Estimated standard errors clustered at the individual level are shown in parentheses. For each school cutoff, optimal bandwidths of the relative GSAT score were derived following Calonico et al. (2017). The model was estimated with linear specifications for both $f(Score_{it})$ and $g(GSAT_{ijt})$. *** p<0.01, ** p<0.05, * p<0.10.

Table A.11: Interactions between PATH and Preferred School Attendance - Optimal Bandwidths and Quadratic Specification of Running Variables

	Boys				Girls			
	Took CSEC	CSEC qualification for tertiary education	Took CAPE	CAPE Associate Degree	Took CSEC	CSEC qualification for tertiary education	Took CAPE	CAPE Associate Degree
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2SLS Parameter Estimates								
Received PATH (β_1)	0.0261**	0.0040	0.0080	0.0039	-0.0002	0.0121	0.0039	0.0047
	(0.0124)	(0.0101)	(0.0076)	(0.0036)	(0.0105)	(0.0123)	(0.0114)	(0.0076)
Attended preferred school (θ_1)	0.0311	0.1257***	0.1047***	0.0710***	-0.0079	0.0802***	0.0809***	0.0927***
	(0.0236)	(0.0142)	(0.0116)	(0.0067)	(0.0134)	(0.0146)	(0.0136)	(0.0086)
Received PATH x Attended preferred school (τ)	-0.0272	-0.0346**	-0.0344***	-0.0187***	0.0098	-0.0060	0.0077	0.0024
	(0.0217)	(0.0142)	(0.0108)	(0.0053)	(0.0171)	(0.0180)	(0.0163)	(0.0101)
Panel B: PATH plus preferred school attendance								
Combined effect ($\beta_1 + \theta_1 + \tau$)	0.0300	0.0951***	0.0783***	0.0563***	0.0016	0.0863***	0.0924***	0.0999***
	(0.0267)	(0.0159)	(0.0124)	(0.0067)	(0.0171)	(0.0177)	(0.0163)	(0.0103)
p-value: ($\theta_1 = \beta_1 + \theta_1 + \tau$)	0.95	0.02	<0.01	<0.01	0.52	0.71	0.44	0.45
Observations	67,661	60,147	61,860	88,166	68,686	65,692	58,013	64,004

Notes: Panel A displays estimated 2SLS coefficients on 'Received' PATH benefits (1), on 'Attend' a preferred secondary school (1), and on their interaction () resulting from equation system (3) - (6) in the text. Panel B displays the addition of the estimated parameters reported in Panel A. Panel B also shows the p-value of the null of equality between the direct school effect and the combined effect adding PATH, school effect, and their interaction. Estimated standard errors clustered at the individual level are shown in parentheses. For each school cutoff, optimal bandwidths of the relative GSAT score were derived following Calonico et al. (2017). The model was estimated with quadratic specifications for both $f(Score_{it})$ and $g(GSAT_{ijt})$. *** p<0.01, ** p<0.05, * p<0.10.

8 Appendix B: The Impact of PATH

PATH eligibility depends on whether the household's PMT score is below a fixed eligibility threshold unknown to potential beneficiaries. If nothing else differs among households scoring just above and below the eligibility threshold, any sudden change in outcomes through the threshold can be attributed to the PATH (Hahn et al., 2001). One can exploit the discontinuity in the likelihood of being a PATH beneficiary through the threshold by estimating the following two-stage least-squares (2SLS) model:

$$Received_{it} = \pi \cdot AboveP_{it} + f_1(Score_{it}) + X_{it}\gamma_1 + \varepsilon_{1,it} \tag{9}$$

$$Y_{it} = \beta \cdot \widehat{Received}_{it} + f_2(Score_{it}) + X_{it}\gamma_2 + \varepsilon_{2,it} \tag{10}$$

In the first stage (9) the model predicts whether individual i who applied for PATH benefits in year t actually received them, $Received_{it}$, as a function of scoring above the PATH eligibility threshold, $AboveP_{it}$, and controls.[28] To account for latent outcomes that vary smoothly through the thresholds, the model controls for a smooth function of the PATH score net of the threshold fully interacted with the $AboveP_{it}$ indicator, $f_1(Score_{it})$.[29] It also controls for parish of residency fixed effects, gender, education of the household member who filed the PATH application, household income, home ownership status, and household size (included in X_{it}). In the second stage (10), the outcome of interest (Y_{it}) is a function of the predicted reception of PATH benefits and all controls from Equation (9). The second stage excluded instrument is $AboveP_{it}$. In this context, estimates of β yield the causal effect of receiving PATH benefits on the outcome of interest.

The key identifying assumption is that nothing other than the change in PATH reception changes in a discontinuous manner through the cutoff. We test this assumption in several ways. We first show that the likelihood of receiving PATH benefits discontinuously changes through the PATH eligibility threshold (Table B.1). The first stage estimates of the $AboveP_{it}$ indicator from equation (9) by gender are reported. Scoring above the cutoff increases the likelihood of receiving PATH benefits by 77 percentage points. By contrast, the socioeconomic composition of households remains smooth through the PATH cutoff. To show this, we follow Kling et al. (2007) and compute a baseline sociodemographic standardized index defined as the equally weighted average of the z-scores of all available sociodemographic variables reported at PATH application.[30] Then we estimate a reduced-form model as in (9) with this standardized index as dependent variable and report the estimates on the $AboveP_{it}$ indicator by gender (Table B.1). Consistent with smoothness through

[28] We use the negative of the PATH PMT score and thresholds in all our specifications.

[29] We use a cubic polynomial.

[30] These variables include parish of residency, gender of the household head, education of the household head, household income, home ownership status, and household size.

the cutoffs, scoring above the PATH cutoff is unrelated with these summary indexes for both boys and girls. In addition, we follow McCrary (2008) and test for a discontinuity in density through the cutoff and find no discontinuity for either boys or girls (Table B.1). These tests suggest that our estimation strategy to estimate PATH effects is likely valid.

We start exploring the direct impacts of PATH, among all PATH applicants, on school progression. To do so, we estimate the 2SLS model outlined in equation system (9)-(10). Table B.2 (Panel A) reports estimates of the β parameter from equation (10) for both boys and girls. We observe positive and significant effects of PATH on the likelihood of taking the GSAT for both boys and girls equivalent to 5- 6.5 percentage points ($p-value$<0.01). About half of these effects are driven by taking the GSAT on time (i.e., before turning 12 years old). Given that taking the GSAT is necessary to be placed in a secondary school, these positive effects indicate an increased intention to continue studying beyond primary school. This intention translates into actual secondary school completion as there are equivalent impacts in terms of CSEC taking (overall and on time). When looking at the likelihood of pursuing post-secondary studies, the impacts on taking the CAPE are diminished with point estimates below 1 percentage point.

We then proceed to measure impacts on secondary and post-secondary learning among those who applied to secondary school (i.e., took the GSAT). Consistent with our main results, Table B.2 (Panel B) shows that there were no direct impacts of PATH on learning.

Table B.1: Validity of the Identification Strategy (All PATH applicants 2001 - 2013, individual-level database)

	Boys	Girls
	(1)	(2)
First stage: received PATH	0.7720***	0.7713***
	(0.0041)	(0.0042)
Exclusion restriction: sociodemographic index	0.0017	0.0031
	(0.0019)	(0.0019)
Differential density at PATH eligibility cutoff	0.9731	0.8481
[p-value]	[0.3305]	[0.3964]
Observations	142,991	137,897

Notes: The table reports first stage estimated coefficients on 'AboveP' from equation (9); estimated coefficients on 'AboveP' having the baseline sociodemographic index as dependent variable within a reduced-form model with the same structure as equation (9); and the results of the McCrary (2008) cutoff manipulation test around the PATH eligibility cutoff. Heteroskedasticity robust estimated standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table B.2: PATH 2SLS Effects on School Progression and Learning

	Boys		Girls	
	Effects	Observa-tions	Effects	Observa-tions
	(1)	(2)	(3)	(4)
Panel A: PATH 2SLS effects on school progression (all PATH applicants)				
Took GSAT	0.0500***	142,991	0.0649***	137,897
	(0.0083)		(0.0076)	
Took GSAT (on time)	0.0306***	142,991	0.0295***	137,897
	(0.0094)		(0.0099)	
Took CSEC	0.0509***	142,991	0.0427***	137,897
	(0.0094)		(0.0096)	
Took CSEC (on time)	0.0268***	142,991	0.0271***	137,897
	(0.0082)		(0.0098)	
Took CAPE	0.0079*	142,991	0.0095	137,897
	(0.0046)		(0.0065)	
Took CAPE (on time)	0.0087**	142,991	0.0101	137,897
	(0.0044)		(0.0064)	
Panel B: PATH 2SLS effects on learning (conditional on taking the GSAT)				
CSEC qualification for tertiary education	0.0040	106,952	-0.0029	113,140
	(0.0076)		(0.0094)	
CSEC qualification for tertiary education (on time)	0.0038	106,952	-0.0042	113,140
	(0.0068)		(0.0088)	
CSEC subjects taken	0.1101	106,952	-0.0722	113,140
	(0.0687)		(0.0741)	
CSEC subjects taken (on time)	0.0630	106,952	-0.0869	113,140
	(0.0651)		(0.0796)	
CSEC subjects passed	0.0877	106,952	-0.0582	113,140
	(0.0587)		(0.0697)	
CSEC subjects passed (on time)	0.0507	106,952	-0.0555	113,140
	(0.0546)		(0.0706)	
CAPE Associate Degree	0.0007	96,171	0.0057	100,975
	(0.0037)		(0.0053)	
CAPE Associate Degree (on time)	0.0011	96,171	0.0056	100,975
	(0.0036)		(0.0053)	
CAPE units taken	0.0115	96,171	0.0050	100,975
	(0.0377)		(0.0502)	
CAPE units taken (on time)	0.0180	96,171	0.0088	100,975
	(0.0371)		(0.0498)	
CAPE units passed	0.0177	96,171	0.0119	100,975
	(0.0346)		(0.0474)	
CAPE units passed (on time)	0.0240	96,171	0.0132	100,975
	(0.0341)		(0.0471)	

Notes: This table displays estimated 2SLS coefficients on 'Received' PATH benefits using 'AboveP' as the excluded instrument (resulting from equation system (9)-(10) in the text). GSAT outcomes on time refer to those measured before the individual turned 12 years old. CSEC outcomes on time refer to those measured within 5 years after GSAT taking. CAPE outcomes on time refer to those measured within 7 years after GSAT taking. Heteroskedasticity robust estimated standard errors are shown in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.10$.