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# The Effect of Consecutive Disasters on Educational Outcomes

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## ABSTRACT

The effect of consecutive natural events on educational outcomes was analyzed by using the case study of Puerto Rico. We describe how school service interruptions related to Hurricane María and the 2020 earthquake sequence affected educational outcomes, especially among vulnerable populations. Our data come from several databases and include individual student information. The empirical analyses include the difference-in-difference method (DD), the Heckman–Copula estimation, Propensity Score Matching, the Cox and Weibull duration regressions, and the Ordinary Least Square (OLS) method. Our analysis suggests that students in severely affected areas, or whose school was permanently closed after the hurricane, have higher probabilities of decreasing their academic achievement and, for some students, dropping out of school after a disaster. We conclude with policy recommendations to increase the capacity to cope with school interruptions due to hurricanes, floods or earthquakes.

**Keywords**: disaster, educational achievement, school dropout rates, duration analysis, hurricane, Puerto Rico

## 1. Introduction

In this paper we present an analysis of the educational outcomes of public-school students in Puerto Rico following exposure to the disasters that have affected the island, including massive hurricanes and earthquakes (due to data limitations, the impacts of the most recent and ongoing COVID pandemic could not be studied fully). A high proportion of public-school students in Puerto Rico live in families with incomes below the federal poverty line and the proportion with disabilities is significantly higher than other areas in the United States. Therefore, we focus on the effects of disasters on educational outcomes (measured by school attrition rate and scores on standardized tests) among a student population that is already characterized by a high level of vulnerability.

Disasters have been found to have a strong emotional, behavioral, and academic impact on children (Gibbs et al., 2019; Gomez & Yoshikawa, 2017; Mohammad and Peek, 2019; Peek et al., 2018; Pane et al., 2008). For instance, Takasaki (2017) finds reductions in male secondary school enrollment among farming families after a disaster. Crespo Cuaresma (2010) reports that geological disasters reduced participation in secondary school, although the effect was not robust for other disasters that were more predictable. Gibbs et al. (2019) found that in primary school, the academic performance in math and reading tests was affected by the level of exposure to wildfires in Australia. The authors suggest that disruption of neural-maturational processes by trauma could have affected their cognition. They also point out the substantial damage to infrastructure and social disruption in schools, which limited the accessibility of teaching facilities. Another study by Liu et al. (2019), found that adolescents affected by the 2010 Yushu earthquake exhibited poor school adaptation five years after the event. This was more evident in males, junior students, and those who did not participate in post-disaster reconstruction activities.

These results point towards the long-lasting effects of disasters on young students and the need for long-term mental health services. Likewise, Nguyen and Pham (2018) found that natural hazards negatively affected children's academic performance and cognitive ability, especially those exposed to floods. Recent evidence on the effect of the COVID-19 pandemic on educational outcomes points to smaller gains in academic abilities in fall 2020 compared to the pre-pandemic year, especially on math skills. In addition, student attrition rates were significantly higher in fall 2020 than the previous year (Kuhfeld et al., 2020).

Few studies focus on the consequences of consecutive disasters on the educational outcomes of children with disabilities. Similarly, the literature on permanent school closures after a disaster is scarce. We aim to fill these gaps in the literature by using the case of Puerto Rico, a US territory hit by two major hurricanes in September 2017, and an earthquake swarm starting in January 2020. One of those hurricanes, Hurricane María, is considered the costliest to have landed in Puerto Rico and the third costliest in US history (National Hurricane Center, 2018). According to official data on school reopening dates, on average, after Hurricane María, schools remained closed for 55 days, and all schools reopened by December 2017. Nevertheless, according to Segarra-Alméstica (2022), 28% of principals surveyed indicated that students started attending school between January and March 2018. Three years later, on January 7, 2020, a 6.4 magnitude earthquake hit the southern part of Puerto Rico, causing the start of the school semester to be postponed for the entire public school system in Puerto Rico. Schools began to open on January 28, 2020, gradually. As of March 16, 2020, when the lockdown began due to the COVID-19 pandemic, 1% of schools were still closed. In most public schools, in-person learning did not start until the first semester of 2021–2022.

In this study, we include data on all public-school students in Puerto Rico and focus on two main educational outcomes. First, we examine the proportion of students that did not complete their studies, also known as attrition or school dropout. Second, we focus on scores on Puerto Rico's standardized tests, which are administered to students throughout the island. Our main research questions were: Has the vulnerability profile for public school system students changed after the disasters affecting Puerto Rico? Does student academic achievement in standardized tests post-Hurricane María vary according to the degree of the impact or the length of school interruption due to the hurricane? Does the probability of school attrition (noncompletion) post-Hurricane María and post-earthquake vary according to the degree of exposure to the damage caused by the disasters?

Schools can be a source of security, hope, and connectivity after a disaster (Mooney et al., 2020) for all students. If schools close and support services are interrupted, we expect student well-being to be compromised. Recent studies found adverse effects on academic achievement from permanent school closures unrelated to natural events (Brummet, 2014; Engberg et al., 2012; Rumberger & Larson, 1998). The literature related to disasters is thinner. Sacerdote (2012) examined the effect on students forced to leave school due to Hurricane Katrina and found that those who relocated to better school districts made up substantial ground after three years. Richardson (2005), however, found that after Katrina, most of the displaced students in her sample performed more poorly in their new school than in the previous one.

On the other hand, educational vulnerability for children with disabilities increases during disasters. Some of the reasons include inadequate school infrastructure to offer them services, a loss of emotional support from teachers, the students' high sensibility to having their routines disrupted, and the loss of documents making assessments difficult (Peek & Stough, 2010).

McAdams Ducy and Stough (2011) also highlight some consequences of educational service interruptions, such as medical and educational service needs, the possible loss of assistive equipment, and loss of academic, social, and life skills.

We structured our investigation around five research hypotheses: Disasters increase student poverty in the most affected areas; Exposure to disasters increases the disability levels in the student population; The length of time of school closures reduces performance on standardized tests; Students with disabilities experience a significantly larger loss in academic outcomes; School attrition (noncompletion) is higher in the municipalities most affected by disasters.

## 2. Data

### 2.1 Socioeconomic Status and Disability

We used several databases for our analysis. The first source is the socioeconomic data from the Puerto Rico Department of Education Student Information System (PRDE–SIS). The Puerto Rico Department of Education (PRDE) collects data on student demographics, including their gender, poverty status, ethnicity, and disabilities. These disabilities are categorized as autism, deafness or blindness, developmental delays, emotional disturbance, hearing impairment, intellectual disability, multiple disabilities, orthopedic impairments, specific learning problems, speech or language impairment, trauma-related brain injury, or visual impairments. Data from the PRDE-SIS was obtained through a data exchange agreement with PRDE that establishes the SIS data's private and confidential nature. We also obtained approval from the University's Internal Review Board to utilize individual student data, and all research team members signed confidentiality agreements.

### 2.2 Academic Achievement

We also used the PRDE-SIS META's results data, specifically Puerto Rico's standardized achievement test (META) for mathematics, English, and Spanish. Students take this test in the third to eighth and eleventh grades. META classifies student achievement using a four-level scale: pre-basic, basic, proficient, and advanced. We transformed these categories into a numeric variable, using a scale from one to four, where one was equivalent to pre-basic level and four to advanced. The scores for the three subjects were averaged to obtain the student's META score. META has two types of tests, including type 1 taken by most students and type 2 for students in full-time special education classrooms. Only the results for the type 1 test were included in the analysis. We also used the PRDE-SIS exit data, which include the reason for leaving school. The most recent data were for March 30, 2021.

### 2.3 Disaster Damage

Identifying the specific effects of Hurricane María and the earthquakes required examining the degree of damage that both events caused at the municipal level and determining the municipalities most affected by each event.[1] We used data from the Open Federal Emergency Management Agency (FEMA) Housing Assistance Program Data–Owner data set. The information was aggregated by disaster number and municipality. The area covered by an emergency declaration varies according to the impact of the disaster. For Hurricane María (disaster declaration #4339), all municipalities were included for Individual and Public Assistance (Categories A–G). Emergency Declaration #4473 was issued to cover the losses from

[1] Puerto Rico is divided into 78 local government jurisdictions or municipalities. Meanwhile, the Puerto Rico Public School System is organized as follows: Secretary (Central Office); Regional Director (seven offices); and schools. However, Puerto Rico Department of Education is considered a State District (PR-01) for federal purposes.

the January 2020 earthquakes. All areas within Puerto Rico were eligible for FEMA's Hazard Mitigation Grant Program, but only 33 municipalities were eligible for individual assistance. Eighteen of those municipalities were also eligible for public assistance.

Using the OpenFema-Owner data set, the Puerto Rico Community Survey (PRCS), and the Census Population Vintage (2022), we created three variables related to disaster damage by municipality for each emergency declaration. They were: (1) the percentage of households whose inspected damage was greater than $10,000; (2) the percentage of households that received a financial grant from FEMA greater than $10,000, and (3) per capita Individual Home Program amount. Two disadvantages of this data were that they exclude nonhomeowners, and localities with a higher home value may also have higher damage dollar amounts. However, the Homeland Security Operational Analysis Center (2020) indicates that accounting for those factors does not significantly affect the measure of relative damage.

The three variables were normalized using the min-max normalization technique. A principal component analysis (PCA) was used to evaluate whether the three variables correspond to one component that can be a composite indicator of damage from each disaster. As expected, the correlation between the FEMA variables for each disaster was remarkably high. The PCA analysis confirms that all three variables belong to the same component and received similar loading. In this case, using the component score or using a simple average of the three normalized variables resulted in the same groupings.

We created a dichotomous variable for "Municipalities Highly Impacted by Hurricane María," defined as those municipalities with a composite indicator for disaster 4339 one standard deviation higher than the mean for all municipalities. The variable is equal to one for municipalities highly impacted by Hurricane María and zero otherwise. Municipalities with a composite indicator within one standard deviation of the mean were categorized as the medium-impact group. Municipalities one standard deviation or more below the mean constituted the least affected group. The 14 municipalities highly impacted by Hurricane María are located in the eastern and central part of the island, as shown in Figure 1.[2]

Similarly, municipalities highly impacted by the January earthquakes were defined as those with a composite indicator for disaster 4,473 one standard deviation above the average for the 33 municipalities that qualified for individual assistance. Three municipalities showed an impact significantly higher than the rest. These were Guayanilla, Guánica, and Yauco. The medium-impact group was composed of the other 30 municipalities that qualified for individual assistance.

## 3. Data Analysis and Research Methods

### 3.1 Measuring the Effect of Hurricane María on Academic Achievement

To identify Hurricane María's effect on academic achievement, we used two approaches: "differences in differences" (DD) and "propensity score matching" (PSM). The analysis uses the DEPR-SIS, which expands from school years 2015–2016 to 2018–2019. The students' socioeconomic data were merged with the data file containing information on META results. We obtained an unbalanced panel data set.

[2] These municipalities are: Aibonito, Barranquitas, Canóvanas, Ciales, Comerío, Corozal, Maunabo, Morovis, Naranjito, Orocovis, Salinas, Vieques, Yabucoa and Jayuya. Alternative groupings estimated using change in nighttime lighting from August 2017 to October 2018 obtained from Homeland Security Operational Analysis Center (2020) as an additional variable in the PCA and using k-mean clustering yields very similar results.

The DD estimates a particular treatment effect as the differences between the change in outcome for the treated and the control group after treatment. In a regression framework, additional independent variables can be added to account for differences in the groups' composition. The treatment is estimated as the parameter β in the following equation.

$$y_{it} = \alpha_0 + \alpha_1 d_t + \alpha_2 d_i + \beta(d_t * d_g) + X_{it}'\delta + \varepsilon_{it} \qquad (1)$$

where $d_t$ is equal to one if the observation corresponds to the post-treatment period and zero otherwise; $d_g$ is equal to one if the observation corresponds to the treatment group and zero otherwise; and $X_{it}$ is a vector of characteristics corresponding to observation *i* in period *t*, which are described in Appendix 1.

In our case, the main treated group was students enrolled in a school located in one of the municipalities highly impacted by Hurricane María during 2017–2018. From here on, we refer to this group of students as Group 1.[3] Given that Hurricane María had a widespread impact on the island, we created an alternative specification that included two treated groups. Group 2 includes students enrolled in municipalities that suffered medium impact from the hurricane. To estimate the effect, we used panel data that include observations from the academic years 2015–2016 to 2018–2019. Since META tests were administered during the second semester of the school year, results for 2017–2018 and 2018–2019 correspond to the post-hurricane period. Additional interactions between groups and the variables time, poverty, and disability status were included to examine disaster effects among the most vulnerable populations. If Hurricane María had a negative effect on student achievement, we expected to find a negative treatment effect, especially for students included in Group 1. The panel data used includes 437,255 observations

[3] The group assignment was done according to the school register in the socioeconomic data files and corresponded to information offered at the beginning of the school year.

corresponding to 147,846 students. Among them, 13% belong to treatment Group 1 and 59.5% to treatment Group 2.

We used a panel data framework, which can be biased by nonrandom attrition. Our panel's attrition comes from students who graduated, students who dropped out of school, students being promoted to grades that do not take the META exams, and those who left the public school system to move to a private school or migrated outside Puerto Rico. Students that completed the eighth or eleventh grade in June 2017 will not have a post-María META score since students do not take the test in the 9th, 10th, or 12th grade. The decision to drop out of school is expected to be related to academic achievement. However, because hurricane María prompted a surge in out-migration, the decision to migrate is expected to be associated with the degree of hurricane-related damage a person faces. Highly impacted areas suffered prolonged periods without water or power and lengthier school interruptions, forcing many to move out. Therefore, attrition can be considered nonrandom, and attrition bias must be addressed.

As suggested by Cheng and Trivedi (2015), we used the Heckman copula (HC) maximum likelihood estimation for sample selection models proposed by Hasabe (2013) to correct for panel attrition bias. This framework allows correcting for sample selection by assuming a fully parametric copula-based approach. The estimation requires specifying the marginal distributions for the attrition and the META scores variables and selecting a specific copula to generate a joint distribution. The estimated model consists of two equations. The first equation is a bivariate sample-selection equation. It includes an indicator variable S, which is equal to 1 if the observation is not lost due to attrition. The vector used the following variables as exclusion restrictions: Municipality median age in 2016, Municipality fertility rate in 2016; Municipality employment rate in 2016; Municipality percentage of owner-occupied households in 2016;

Municipality percentage that travel time to work is greater than 30 minutes; Hurricane María High Impact variable (in Group 1) and Hurricane María Medium Impact variable (in Group 2); Length of school interruption; Female; Household Income below poverty threshold; Presence of disability; Non-Puerto Rican Hispanic; Other non-Puerto Rican; School poverty; and Rural school zone.

$$S_i = \begin{cases} 0 \ if \ S_i^* = Z_i\gamma + \omega_{si} \leq 0 \\ 1 \ if \ S_i^* = Z_i\gamma + \omega_{si} > 0 \end{cases} \tag{2}$$

The second equation estimates the DD model for those observations that remained in the sample.

$$S_i = \begin{cases} y_{it} = \alpha_0 + \alpha_1 d_t + \alpha_2 d_i + \beta(d_t * d_g) + X_{it}'\delta + u_{it} & if \ S = 1 \\ . & if \ S = 0 \end{cases} \tag{3}$$

The model is estimated through maximum likelihood, assuming a joint probability for the error terms $u_{it}$ and $\omega_{si}$.

The models can be estimated under different assumptions. A post-estimation analysis can determine the preferred specification. We estimated various DD models using two different attrition definitions, with and without exclusion restrictions, and seven different copula specifications. A preferred model was selected according to the Akaike Information Criterion (AIC), as suggested by Hasabe (2013). In the preferred specification, attrition is equal to 1 if the student has a META score in the pre-María period, but no score post-María, and zero if the student has at least one score in each period; the attrition equation includes variables pertaining to the municipality where the students were enrolled during 2015–2016; and a Joe copula specification is used. These municipal variables include demographic and economic aspects that may influence mobility and were obtained from the PRCS 2016 five-year sample. The DD model equation dependent variable is the student META score for each year. The control variables included in the DD equation are the following: (a) post-treatment dummy (post-María identified observations corresponding to the post-Hurricane María period); (b) treatment group dummies (Group 1 correspond to Hurricane María High Impact and Group 2 to Hurricane María Medium Impact); (c) treatment effect dummies (interaction between the post-treatment and the treatment groups dummies; (d) Length of school interruption (interaction between the post-María dummy and the number of days the school was officially closed after Hurricane María); (e) individual characteristics (sex, school grade dummies, income poverty status, presences of disability, Non-Puerto Rican Hispanic, Other Non-Puerto Rican; (f) school characteristics (School Income Poverty Headcount and Rural zone identifier); (g) interactions between post-María with poverty and disability indicators; and (h) interactions between the treatment effects and the poverty and disability indicator.

Another way we dealt with sample attrition problems was by using only post-treatment observations and PSM to estimate the effect. The PSM is applied when measuring a treatment effect using only post-treatment data. It compares the outcome for observations in the treatment groups with similar observations from the control group, using the following covariates to match them: poverty; disability; school poverty; sex; school grade; non-Puerto Rican Hispanic; other non-Puerto Rican; household size; rural; and length of school interruption. Therefore, it identifies whether the META scores for students in the treatment group were significantly different from those in the control groups. This method only considers one treatment group and does not measure other covariates' effects or their interrelation. Nevertheless, it was a helpful robustness check on our results.

In addition to the substantial number of public schools closed due to austerity measures, 22 schools closed during 2017–2018 due to Hurricane María. These 22 schools were opened and had students enrolled as of September 2017 but did not reopen after the hurricane. We addressed whether students whose schools closed due to the hurricane had more academic difficulties than the rest of the student body. The dependent variable was the interannual changes in META test scores. We were not trying to explain whether some students did better than others in absolute terms or measure the total academic achievement of each student. Instead, we measured whether students performed worse than during the previous time period. If external factors affected the average META test score every year, it would be difficult to associate such external factors to interannual variations in the average academic performance of all students. We performed two OLS estimations for students that took the META test to measure whether the change in average META score from 2017 to 2019 was significantly different for students enrolled in the 22 closed schools after Hurricane María (the treatment group in this case) and all other students. To isolate and identify the effects of school closing, we include the covariates age, number of family members, poverty level, sex, and whether the student attends a school in a *main productive municipality* in our estimations. The economic activity or productivity per municipality was calculated as in Caraballo-Cueto (2017), where each county's share of economic activity in the Economic Census was then extrapolated to a Gross National Product per county.

### 3.2 Measuring the Effect of Natural Hazard Events on Students' Attrition Rate

We used duration analysis to measure the effect of Hurricane María and the earthquake on the probability of dropping out of school. We assessed whether Hurricane María affected the risk of dropping out of school for two cohorts of students enrolled in the public school system on 15 September 2017, specifically those in the eighth and tenth grades. From here on, they will be referred to as the "2018 cohorts." The 2018 eighth-grade cohort included 21,883 students, with an attrition rate of 4.15%, while the tenth-grade cohort comprised 20,750 students with an attrition rate of 4.37%. The variable of interest is the days taken to drop out, measured as the number of days between the exit date recorded in the DEPR-SIS and 15 September 2017. Similarly, we looked at the earthquake's effect on students enrolled in the eighth and tenth grades on 31 December 2019. The eighth and tenth-grade cohorts included 19,700 and 18,533 students, with an attrition rate of 0.75% and 0.58%, respectively. From here on, they will be referred to as the "2020 cohorts." Students who graduated or remained active at the end of the analysis period are considered right-censored observations. Due to graduation, the 2018 10th-grade cohort's observations were right-censored on June 30, 2020. All other cohorts were censored on 30 March 2021 (the last date of available data).

Duration analysis estimates the conditional probabilities of dropping out given that the student is still active at time t; this is called the "hazard function." It estimates the probability of students leaving school at any given time, given that they stay in school up to that point, conditional on covariates (X).

$$h(t, X) = \frac{f(t|X)}{1-F(t|X)}, \tag{4}$$

where f is the density function, and F is the cumulative function. The hazard function can be estimated using a semi-parametric Cox regression or a parametric model, controlling for covariates. The Cox model assumes that hazard rate ratios are proportional across observations through time, defining the hazard function as:

$$h(t|X) = \lambda(t) \exp(X'\beta), \tag{5}$$

where λ(t) is the baseline hazard function.

Parametric models require specific distributional assumptions about the data. A chi-squared test for the proportionality assumption allows for testing whether the proportionality condition is met. Under the null hypothesis of no proportionality, a p-value under 0.05 implies that the condition is not met. In the case of parametric models, the AIC can be used to select the best-fitted model. We estimated the hazard functions for dropping out of school for each cohort using the Cox regression and a parametric regression assuming a Weibull distribution.[4] The Weibull distribution hazard function is given by:

$$h(t|X) = \rho\lambda^{\rho}t^{\rho-1}, \text{ where } \lambda = \exp(X'\beta). \quad (6)$$

Regressions for the 2018 cohorts include a dichotomous variable to identify students enrolled in municipalities highly impacted by Hurricane María. Another one identified those enrolled in municipalities that suffer medium impact. Therefore, their hazard risk is measured in comparison to the low-impact group. Likewise, the 2020 cohorts' analyses include variables to identify students in municipalities with high and medium impact from the earthquakes. The semiparametric Cox model and the Weibull parametric models include as covariates the following: sex; poverty status; presence of disability; previous META score; non-Puerto Rican, school poverty head count; and a rural school dummy variable.

## 4. Findings

### 4.1 Characteristics of the Student Population

[4] The Weibull distribution was selected because it is recognized as a flexible functional form, and in our case also tends to have lower Akaike Information Criteria compared to other distributions across the different cohort estimations.

Table 1 shows some of the variables included in the DEPR data. The average student age was 11.4, and 1.3% of students attended a school permanently closed after Hurricane María. There appears to be a declining trend in the META tests across the years. Roughly half of the student population were female students and this proportion remained consistent throughout 2014–2020. The average number of family members was 3.86, and 36% of the students lived in cities with a relatively high economic output, as defined in Caraballo-Cueto (2017).

Around 80% of students in the public school system have a family income below the poverty level, but that incidence is not static. The pattern suggests that the proportion of students living below the poverty level decreased from 80.8% in 2014 to 77.2% in 2017, the year of Hurricane María, and then increased to 81.9% by 2020. Figure 2 shows changes in the proportion of students living below the poverty level over time by municipal clusters. The first cluster includes municipalities that received a *high impact* from Hurricane María; the second cluster contains municipalities that experienced *medium impacts*, and the third cluster includes municipalities that suffered only a *low impact*. It was essential to highlight that all municipalities were affected by Hurricanes Irma and María. However, the extent of the devastation, and the time it took to re-establish services, showed some variation.

As shown in Figure 3, there was an inverse relationship between students' poverty level and the level of impact from Hurricane María by municipality. The pattern of poverty reduction between 2014 and 2017 and a subsequent increase between 2017 and 2020 was observed among the three municipality clusters. The data show how the municipalities that experienced the highest impacts from Hurricanes Irma and María saw the sharpest increase in student poverty levels between 2017 and 2020. The poverty rate for municipalities in the high-impact group was almost 2.7 percentage points lower in 2014 (79.9%) than for municipalities in the low-impact group (81.6%). Still, by 2020 both groups had essentially the same poverty rate at 82.2%.

The impact of the 2020 earthquakes on student poverty levels was less evident by municipality clusters. The observed increases in poverty level, particularly between the 2019 and 2020 academic years, were slightly higher for municipalities with a medium or low impact than those with the highest impact from the 2020 earthquakes.

The proportion of public-school students reporting a disability remained relatively stable between 2014 and 2020 at between 28.9% and 30.3% of the total, respectively. We observed that a significantly higher proportion of males reported at least one disability for that same period. The data suggests that more than one in three male students and about one in five female students reported at least one disability. The most reported disability among public school students in Puerto Rico was specific learning challenges (44.6% overall), followed by speech or language difficulties (22.6%). Other health issues were reported by 21.1%, and a relatively small percentage of cases reported health-related mental problems (4.1%), autism (4.3%), emotional challenges (1.3%), auditory or visual impediments (.9%), multiple impediments (.9%), and brain or orthopedic disabilities (.3%). The proportion of students reporting other health challenges increased significantly. It rose from 1.4 to 2.7 for every 10 students reporting a disability between 2014 and 2020.

Municipalities facing low- or medium-impact levels during the earthquakes had a higher proportion of students reporting a disability than municipalities with higher earthquake impacts. The changes between 2014 and 2020 were similar across the three municipality clusters. In fact, the gap between municipality clusters seems to be slightly larger in 2020 compared to 2014, suggesting that there was no relationship between the earthquake damage in the 2019–2020 academic year and the increase in the proportion of students reporting a disability in 2020–2021.

While the proportion of students reporting a disability did not increase significantly based on exposure to Hurricane María or the 2020 earthquakes, it is essential to point out that the overall profile of public-school students in Puerto Rico shows exceptionally high levels of vulnerability due to poverty, disability, and their combined effects. Overall, only about 15.7% of Puerto Rico's public school system students were neither poor nor disabled. In contrast, about 4.9% of Puerto Rico's public education system students were not poor but were disabled; 54.7% were poor and not disabled, while 24.7% of the public-school students were poor and reported at least one learning-related disability.

### 4.2 Regression Results

The results of the DD estimation, shown in Table 2, used the Heckman copula (HC) models to correct for attrition bias. Since the Wald test statistic has a *p*-value smaller than 0.05, the assumption of independence between the attrition and the META scores regression was rejected. Therefore, selection correction was required. The first two models define only one treatment group (students enrolled at the time of the hurricane in highly impacted municipalities), while the last two models include both treatment groups. The treatment effect for Group 1 was negative and statistically significant in three of the four models. The average score for Group 1 reflects a 3% reduction compared to the entire sample.

When we include the length of school interruption in the analysis, the size and significance of the treatment effects for Group 1 decreased, suggesting that the negative effect on academic achievement in highly impacted municipalities was partly related to the amount of time the schools were closed. The treatment effect for Group 2 was not significant. Models HC3 and HC4 show that post-María META scores decreased for students with disabilities and students living in poverty regardless of whether they were included in one of the treatment groups. Puerto Rico's dire fiscal conditions and school closures had been affecting the school system prior to Hurricanes Irma and María, so we might expect those to impact the vulnerable student populations. Nevertheless, students in vulnerable populations in both treatment groups experienced an additional reduction in META scores of approximately 3% to 4%. The coefficients for the additional independent variables had the expected effect.

The PSM results presented in Table 3 confirmed the negative impact of Hurricane María on META scores for students in treatment Group 1. However, the magnitude was smaller than the estimate from the HC results. The table presents the average treatment effect on the treated (ATET). The models were estimated using the last two years of data grouped and separately. Models PSM 4–6 add the length of school interruption as a covariate. Doing so reduces the ATET by 22% for observations in 2018 and 62% for observations in 2019. Models PSM 7-9 and PSM 10–12 repeated the analysis limiting the sample to students living in poverty or students with disabilities, respectively. We measured the size of the ATET as a percentage of the average META score for each model. The treatment effect size ranges between -1.5% and -2.5% for the entire sample, -1% to -1.2% for students living in poverty, and -2.1% to -3.2% for students with disabilities.

We also found that students who suffered a school closure because of Hurricane María had lower academic achievement than the rest. The analysis includes 85,335 observations corresponding to students that participated in META tests in 2017 and 2019. Table 4 shows some of the variables included in the PRDE data for this sample. The average student age was 11.4, and 1.3% of students attended a school permanently closed after Hurricane María. Regression results are shown in Table 4. This decline in academic achievement fluctuated between 14% and 20% of the average change in score. Our results were consistent across different specifications. This estimate was found after controlling for the student sex, poverty, age, family size, and main productive cities.

### 4.3 Duration Model Results

Table 5 presents the results for the Cox and Weibull duration model regressions for the four cohorts used to measure the effect of disasters on dropout rates. The hazard ratio measured the group's relative dropout hazard risk. A ratio greater than 1 implied that the group was more at risk, while a ratio of 1 or less suggests a lower dropout risk. Figure 4 illustrates the cumulative hazard functions for each cohort divided by groups according to disaster impact. For the 2018 cohorts, the proportional hazard assumption was not met. Nevertheless, the results of the parametric regression were very similar to the Cox regression.

Among the 2018 cohorts, the eighth graders in highly impacted municipalities showed no significant effect. However, at any given time, students in the medium-impact group were 18% more likely to drop out than students in the low-impact group. Contrary to expectations, the 10th graders in the most impacted group had a lower dropout hazard risk, meaning that at any point after María, they were less likely to drop out than the low-impact group. They are also less likely to drop out when compared to all other groups. For this cohort, the low-impact group had the highest hazard ratio. Overall, Hurricane María seemed to put more at-risk middle school students in the medium-impact municipalities.

After the 2020 earthquake, eighth graders had a dropout hazard risk twice as high for students in the most impacted municipalities than those in the least affected. The bottom left panel in Figure 4 clearly shows a higher hazard function for the high-impact group, while the other two groups' functions were remarkably similar. Among the 10th graders, the dropout hazard risk was significantly higher for students in the medium-impact group. The difference between the high-impact group's hazard function and the low-impact group's function was not statistically significant.

A competing risk model was estimated for all cohorts to assess whether the estimates may reflect bias caused by attrition due to migration. These models calculated the hazard ratio, considering students might exit the school system for reasons other than the event under study. The results were consistent with those presented in Table 5. We conclude that the effect estimated was not biased due to migration.

## 5. Discussion

The lack of continuity and declining quality of educational services contributed to Puerto Rico's emigration level. The decrease in the quality of education is shown by the continuous decline in the average scores on the META achievement tests. Overall, we found that Hurricane María had a statistically significant but moderate adverse effect on academic achievement. The length of school interruptions partially explained this effect, as well as the proximity of the students to high-impact areas. However, other unknown factors also contributed to decreased levels of academic achievement. These factors may relate to emotional impacts from disaster events, as explored by Lai et al. (2017) and Liu et al. (2019), or services discontinuity. School interruptions affect students' access to food, especially when 80% of students live in households with an income below the poverty line. When schools are not operating, access to adequate nutrition for poor students is limited. In addition, school interruptions affect access to health and social services, which are crucial in times of increased emotional stress, especially for students with disabilities.

Consistent with the arguments of Peek and Stough (2010) and McAdams Ducy and Stough (2011), the adverse effects of Hurricane María on academic achievement were accentuated for students with disabilities in both highly and moderately impacted municipalities. This is important because a significant number of students in the school system reported at least one major disability.

In the HC estimation, the length of school interruption has a positive effect on attrition and a negative effect on the META score, both statistically significant. Since META test scores were unavailable for 2020 and 2021, we could not estimate the effect of school interruption due to seismic activity or COVID-19 on academic achievement. Nonetheless, from our analysis after hurricane María, we can predict significant reductions in academic performance and school enrollment due to dropouts, exits to private schools, and migration. The previously cited literature found that unannounced phenomena, such as geological events, have more significant effects on academic performance. Therefore, the seismic activity can be expected to significantly decrease achievement, especially for the students on the southern part of the Island.

Another aspect that should be considered is the high poverty levels among the public-school student population. Not only is poverty one of the strongest predictors of academic achievement, but we also found that the negative effect of Hurricane María on academic achievement was more substantial for impoverished students.

As evidenced by Takasaki (2017) and Crespo Curesma (2010), exposure to socio-natural disasters can reduce school enrollment. Overall, eighth graders seem more adversely affected by disasters than tenth graders. This finding was consistent with Segarra-Alméstica's (2020) results on poverty being closely related to high school dropout rates, while middle school dropout rates were associated with other risk factors. This argument is consistent with Lie et al.'s (2019) finding to the effect that students who did not participate in post-disaster reconstruction activities had poorer school adaptation.

We also found that for students after hurricane María and high school students after the earthquakes, those in the medium-impact areas showed an increased probability of attrition. One possible explanation is that communities in medium-impacted municipalities did not receive as much attention and support as those in high-impacted municipalities. Schools' support came from municipal governments, churches, the U.S. Army, Puerto Ricans in the U.S., private companies, and other non-governmental organizations (Enchautegui at al. 2018). It might be the case that non-government institutions focused on helping the high-impacted municipalities, leaving the medium-impact municipalities essentially in the hands of municipal governments, which traditionally have limited resources.

In the aftermath of each event, the PRDE has been overly cautious about reopening schools. Following Hurricane María, schools had to wait for the PRDE authorization to resume classes even though, in many cases, the school communities, in collaboration with municipal governments, cleaned and conditioned the schools. After the January 2020 earthquake, all schools in Puerto Rico were inspected and certified, a process that took two months. During the COVID-19 pandemic, most schools in Puerto Rico did not restart in-person learning until August 2021.

The PRDE recognized the need for resilient schools as the first pillar of its infrastructure plan (Puerto Rico Department of Education, March 2022). The plan calls for investments in structural reinforcements in existing school buildings, alternative power sources and water tanks, and classroom technologies to strengthen both in-person and online learning. Nevertheless, an investigation conducted by the Center for Investigative Journalism revealed that the first contracts to provide schools with generators and water tanks were signed in 2020 and, as of October 2022, a minority of schools had generators and water tanks (Diaz Ramos, 2022).

## 6. Conclusion and Policy Recommendations

We found that standardized test scores for students enrolled in 2017–18 in municipalities highly impacted by Hurricane María experienced a significant decrease compared to other groups. Vulnerable students (by poverty or disability) in medium- and high-impact municipalities have experienced an additional reduction in test scores to those students whose schools closed permanently due to damage caused by Hurricane María. After María, the dropout risk was 18% higher for eighth graders in the medium-impact group. Following the earthquake, the dropout risk for eighth graders in the municipalities most impacted by the earthquake was twice as high as for the less affected group. Among tenth graders, the dropout hazard risk was significantly higher for students in the medium-impact group.

Given that natural hazards undoubtedly will keep affecting this and other jurisdictions, policymakers urgently need to develop and implement programs to improve the response to disasters, especially for students with disabilities. For them, a school interruption means much more than not receiving an education. School is where they receive therapies and specialized health services. School personnel often play a leading role in assessing their needs and managing their health struggles. If the education system does not improve its ability to reopen and re-establish services quickly after a disaster, the number of school-age children will continue to decline due to migration. The absence of effective strategies to lower dropout rates and reduce the number of students who receive failing grades poses additional challenges. Enchautegui et al. (2018) described initiatives taken by some school staff, such as visits to students, helping in the distribution of food and water in communities, and being more flexible when students returned to school (e.g. allowing students to attend school without uniforms, no homework that required the use of electricity, and different time schedules, among others). These initiatives should be adopted as part of the schools' emergency response protocols.

Future studies can evaluate specific school policies and dynamics influencing attrition among high school and middle school students in high-impact municipalities. Similarly, future research may develop a learning model that can be activated after disasters. The online or hybrid learning model used during the pandemic, and the infrastructure needed to reach all students, should be improved to help teachers and students resume their educational activities as soon as possible.

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**Appendix 1**

| **List of independent variables and definitions** | |
|---|---|
| **Independent variables** | |
| Post-Maria | Equal to 1 if the META score corresponds to academic year 2017–2018 or 2018–2019 |
| Group1– high impact | Equal to 1 if the student was enrolled in a highly impacted municipality in 2017–2018 |
| Group2 – medium impact | Equal to 1 if the student was enrolled in a medium-impact municipality in 2017–2018 |
| Group1 – post-María (treatment effect) | Group1 * post-María |
| Group2 – post-María (treatment effect) | Interaction of post-María and Group2 |
| Length of school interruption | Days between 15 September 2017 (last day of school before María and the day that the school opened according to the official listing provided by PRDE) |
| Poverty | Equal to 1 if the student lives in a household with income below the poverty threshold |
| Disability | Equal to 1 if the student record includes one major disability |

| | |
|---|---|
| Poverty post-Maria | Poverty * post-María |
| Disability-post-María | Disability* post-María |
| g1– poverty – post-María | Poverty * post-María * Group1 |
| g1– df – post- María | Disability* post-María * Group1 |
| g2 – poverty – post-María | Poverty * post-María * Group2 |
| g2 – disability-post-María | Disability* post-María * Group2 |
| Female | Equal to 1 if sex is female |
| Non-Puerto Rican Hispanic | Equal to 1 if the student is Hispanic but not Puerto Rican |
| Other non-Puerto Rican | Equal to 1 if the student is not Hispanic |
| School poverty | Percentage of students in the school living in households with income under the poverty threshold |
| Rural school zone | Equal to 1 if the school is located in a rural zone |
| **Municipal variables in attrition equation** | |
| Municipality median age in 2016 | Median age in the municipality |

| | |
|---|---|
| Municipality fertility rate in 2016 | Percentage of women aged 15 to 50 that gave birth during the previous 12 months |
| Municipality employment rate in 2016 | Percentage of civilian population aged 25 to 54 employed |
| Municipality % of owner-occupied households in 2016 | Percentage of owner-occupied housing units |
| Travel time to work | Percentage of workers aged 16 and over, not working at home, that reported commute time to work of 30 minutes or longer |

Table 1. Descriptive Statistics of Variables, 2017-2019

| Variables | Average/ Proportion | Standard Deviation | Observations |
|---|---|---|---|
| Age | 11.44 | 1.34 | 85,335 |
| Displaced by María | 0.013 | 0.11 | 85,335 |
| Average in META 2019 | 2.19 | 0.77 | 85,335 |
| Average in META 2017 | 2.605 | 0.85 | 85,335 |
| Proportion of females | 0.515 | 0.50 | 85,335 |
| Number of family members | 3.86 | 1.16 | 85,335 |
| Proportion of students in main cities | 0.36 | 0.48 | 85,335 |
| Poverty Rate | 0.80 | 0.40 | 85,335 |

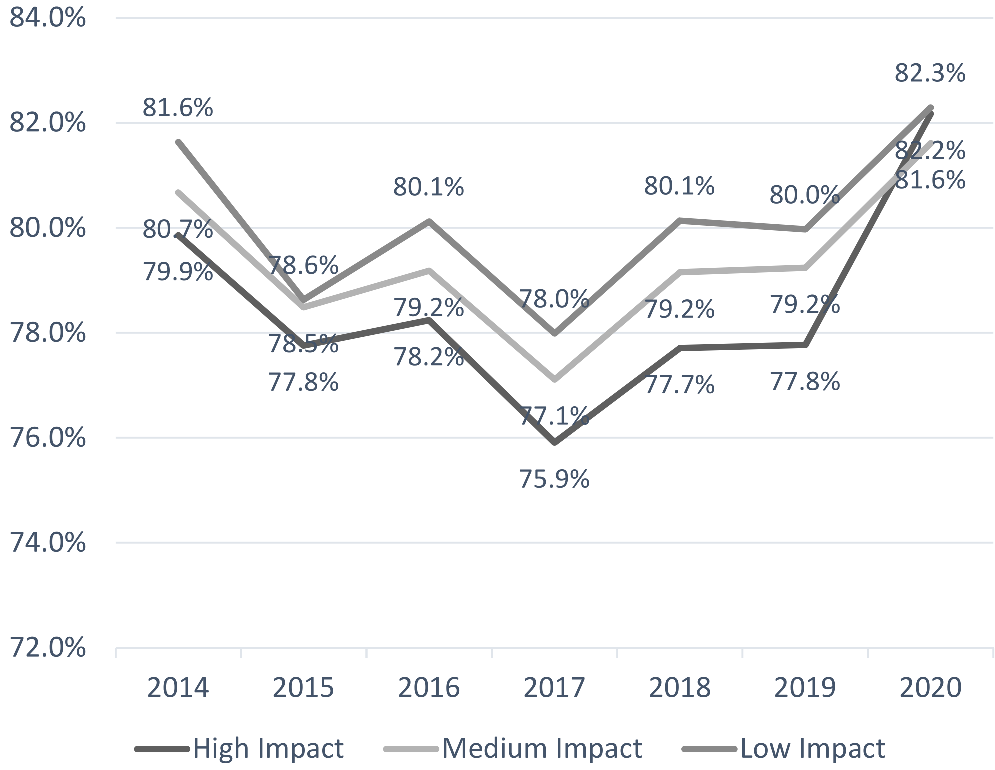
Notes: The years refer to the fiscal period ending in June. Only valid observations with all the entries available are shown.

Source: Authors' calculations based on the Department of Education (2020)

**Figure 1.** Impact Level of Hurricane María on Municipalities in Puerto Rico

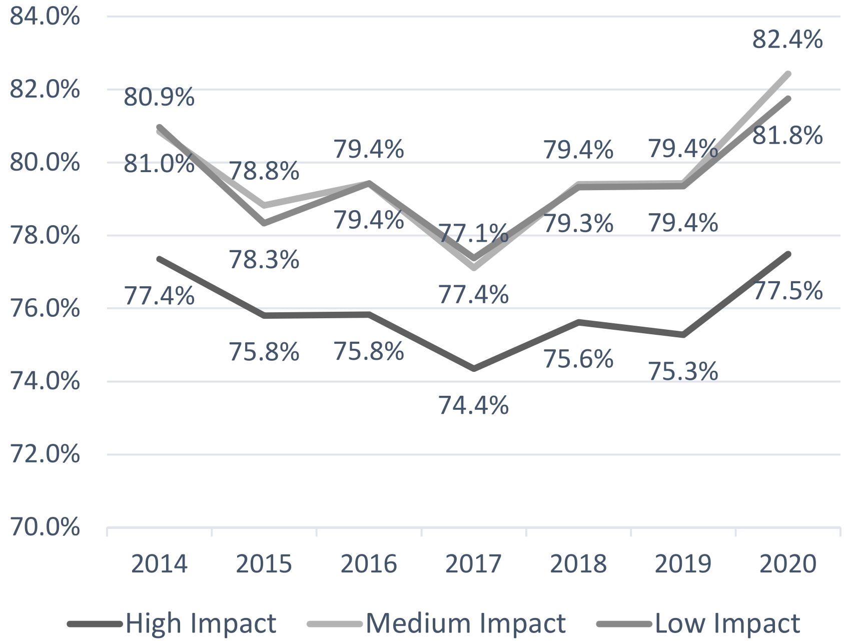

Source: Authors' calculations based on the OpenFema Housing Assistance Program Data (2021)

**Figure 2.** Poverty Level Before and After Hurricane María by Municipal Clusters, 2014–2020




Source: Authors' calculations based on the OpenFema Housing Assistance Program Data and DE (2021)

**Figure 3.** Poverty Level Before and After Earthquake by Municipal Clusters, 2014–2020




Source: Authors' calculations based on the OpenFema Housing Assistance Program Data and the DE (2021)

Table 2. Heckman-Copula Estimation Results

Dependent Variable: Student's Average META Score

| | Model (HC 1) | | Model (HC 2) | | Model (HC 3) | | Model (HC 4) | |
|---|---|---|---|---|---|---|---|---|
| n | | 437,255 | | 433,192 | | 437,255 | | 433,192 |
| clusters | | 147,846 | | 146,701 | | 147,846 | | 146,701 |
| Attrition equation | | | | | | | | |
| Attrition=1 if data include a meta score for the student pre–Hurricane María but none post-hurricane. | | | | | | | | |
| | coef. | p-value | coef. | p-value | coef. | p-value | coef. | p-value |
| Municipality median age in 2016 | -0.0052** | 0.023 | -0.0040* | 0.082 | -0.0025 | 0.309 | -0.0015 | 0.535 |
| Municipality fertility rate in 2016 | -0.0038 | 0.328 | -0.0032 | 0.406 | -0.0024 | 0.549 | -0.0019 | 0.632 |
| Municipality employment rate in 2016 | -0.0017** | 0.004 | -0.0018** | 0.003 | -0.0012** | 0.049 | -0.0013** | 0.033 |
| Municipality % of owner-occupied households in 2016 | -0.0017** | 0.000 | -0.0019** | 0.001 | -0.0022** | 0.000 | -0.0024** | 0.000 |
| Municipality % Travel Time to Work>30 minutes | 0.7005** | 0.000 | 0.6988** | 0.000 | 0.6579** | 0.000 | 0.6607** | 0.000 |
| Group1 -María High Impact | -0.0096 | 0.446 | -0.0159 | 0.206 | 0.0354** | 0.037 | 0.0258 | 0.129 |
| Group2- María Medium Impact | | | | | 0.0454** | 0.000 | 0.0423** | 0.000 |
| Length of school interruption | | | 0.0006** | 0.000 | | | 0.0006** | 0.000 |
| Female | 0.0228** | 0.002 | 0.0228** | 0.003 | 0.0228** | 0.002 | 0.0228** | 0.003 |
| HH Income below Poverty Threshold | -0.0179** | 0.034 | -0.0179** | 0.034 | -0.0181** | 0.032 | -0.0181** | 0.032 |
| Presence of Disability | -0.0884** | 0.000 | -0.0878** | 0.000 | -0.0883** | 0.000 | -0.0878** | 0.000 |
| Non-Puerto Rican Hispanic | 0.0775** | 0.009 | 0.0783** | 0.008 | 0.0806** | 0.006 | 0.0813** | 0.006 |
| Other non-Puerto Rican | 0.0269 | 0.728 | 0.0270 | 0.727 | 0.0286 | 0.713 | 0.0284 | 0.714 |
| School poverty | -1.7668** | 0.000 | -1.7458** | 0.000 | -1.7693** | 0.000 | -1.7488** | 0.000 |
| Rural school zone | -0.3134** | 0.000 | -0.3031** | 0.000 | -0.3163 | 0.000 | -0.3061** | 0.000 |
| constant | 0.6073** | 0.000 | 0.5459** | 0.000 | 0.4751 | 0.000 | 0.4274** | 0.000 |
| Dependent variable: Student's Average META score | | | | | | | | |
| | coef. | p-value | coef. | p-value | coef. | p-value | coef. | p-value |
| post María | 0.2163** | 0.000 | 0.2884** | 0.000 | 0.2208** | 0.000 | 0.3387** | 0.000 |
| Group1 -high impact | 0.0445** | 0.000 | 0.0434** | 0.001 | 0.1360** | 0.000 | 0.1349** | 0.000 |
| Group2- medium impact | | | | | 0.1294** | 0.000 | 0.1346** | 0.000 |
| Group1_post María (treatment effect) | -0.0651** | 0.024 | -0.0549* | 0.059 | -0.0739** | 0.023 | -0.0439 | 0.187 |
| Group2_post María (treatment effect) | | | | | -0.0121 | 0.588 | 0.0045 | 0.843 |
| Length of school interruption | | | -0.0012** | 0.010 | | | -0.0023** | 0.000 |
| HH Income below Poverty Threshold | -0.1866** | 0.000 | -0.1867** | 0.000 | -0.1867** | 0.000 | -0.1869** | 0.000 |
| Presence of Disability | -0.3864** | 0.000 | -0.3863** | 0.000 | -0.3849** | 0.000 | -0.3847** | 0.000 |
| Poverty post María | -0.0269** | 0.040 | -0.0265** | 0.043 | 0.0100 | 0.639 | 0.0086 | 0.687 |
| Disability post María | -0.1614** | 0.000 | -0.1629** | 0.000 | -0.1062** | 0.000 | -0.1111** | 0.000 |
| Group1*poverty*post María | -0.0534* | 0.104 | -0.0529 | 0.107 | -0.0890** | 0.016 | -0.0859** | 0.020 |
| Group1 * disability*post María | -0.0429 | 0.152 | -0.0411 | 0.169 | -0.0991** | 0.003 | -0.0936** | 0.005 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Group2 * poverty* post María | | | | | -0.0511** | 0.048 | -0.0483* | 0.062 |
| Group2 *disability*post María | | | | | -0.0780** | 0.001 | -0.0730** | 0.002 |
| | | | | | | | | |
| Female | 0.1432** | 0.000 | 0.1429 | 0.000 | 0.1443** | 0.000 | 0.1440** | 0.000 |
| Non-Puerto Rican Hispanic | 0.0473 | 0.112 | 0.0464 | 0.119 | 0.0662** | 0.025 | 0.0655** | 0.026 |
| Other non-Puerto Rican | 0.0254 | 0.747 | 0.0245 | 0.756 | 0.0259 | 0.742 | 0.0245 | 0.755 |
| School Poverty Headcount | -1.7837** | 0.000 | -1.7791 | 0.000 | -1.8131** | 0.000 | -1.8070** | 0.000 |
| Rural School Zone | 0.0248** | 0.001 | 0.0256 | 0.000 | 0.0103 | 0.166 | 0.0106 | 0.152 |
| constant | 3.4597** | 0.000 | 3.4525 | 0.000 | 3.3939** | 0.000 | 3.3856** | 0.000 |
| | | | | | | | | |
| Wald test of independence | 632.5** | 0.000 | 623.9 | 0.000 | 652.2** | 0.000 | 645.3** | 0.000 |

Note: All models presented include school grade indicator variables.
* Significant at a 0.10 level
**Significant at a 0.05 level
Source: Authors' calculations based on the OpenFema Housing Assistance Program Data and the DE (2021)

Table 3. PSM Results

| Dependent Variable: Student's average META Score.<br>Treatment Model: logit<br>Treatment Group 1 = enrolled in a highly impacted municipality in academic year 2017-2018 | | | | | | |
|---|---|---|---|---|---|---|
| | Years Included | Students Included | Covariates: | # of Observations | ATET | p-value |
| Model (PSM 1) | 2018 and 2019 | All | poverty, disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural, year. | 313,023 | -0.0363** | 0.000 |
| Model (PSM 2) | 2018 | All | poverty, disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural | 162,588 | -0.0499** | 0.000 |
| Model (PSM 3) | 2019 | All | poverty, disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural | 150,435 | -0.0584** | 0.000 |
| Model (PSM 4) | 2018 and 2019 | All | poverty, disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural, year, length of school interruption. | 309,101 | -0.0274** | 0.000 |
| Model (PSM 5) | 2018 | All | poverty, disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural, length of school interruption. | 160,657 | -0.0387** | 0.001 |
| Model (PSM 6) | 2019 | All | poverty, disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural, length of school interruption. | 148,444 | -0.0220* | 0.068 |
| Model (PSM 7) | 2018 and 2019 | students living in households with income under the poverty threshold | disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural, year. | 245,853 | -0.0280** | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Model (PSM 8) | 2018 | students living in households with income under the poverty threshold | disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural | 126,426 | -0.0272** | 0.031 |
| Model (PSM 9) | 2019 | students living in households with income under the poverty threshold | disability, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural | 119,427 | -0.0222* | 0.073 |
| Model (PSM 10) | 2018 and 2019 | students with disabilities | poverty, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural, year. | 98,793 | -0.0466** | 0.000 |
| Model (PSM 11) | 2018 | students with disabilities | poverty, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural | 50,959 | -0.0456** | 0.012 |
| Model (PSM 12) | 2019 | students with disabilities | poverty, school poverty, sex, school grade, non-Puerto Rican Hispanic, other non-Puerto Rican, household size, rural | 47,834 | -0.0668** | 0.000 |

* Significant at a 0.10 level
**Significant at a 0.05 level
Source: Authors' calculations based on the OpenFema Housing Assistance Program Data and the DE (2021)

Table 4. OLS Estimation, Academic Impact of Hurricane María on Displaced Students

| | Dependent variable: (2019 Average Score in standardized test – 2017 Average Score in standardized test) | | |
|---|---|---|---|
| School Closed by Hurricane María | -0.085*** | -0.06** | -0.06** |
| | (0.025) | (0.024) | (0.024) |
| Poverty Level | -0.067*** | -0.075*** | -0.075*** |
| | (0.007) | (0.007) | (0.007) |
| Main Productive Cities | 0.028*** | 0.024*** | 0.024*** |
| | (.006) | (.006) | (.006) |
| Sex | -0.054*** | -0.06*** | -0.06*** |
| | (0.0055) | (0.0055) | (0.0055) |
| Age | | | |
| | | 0.07*** | 0.07*** |
| | | (0.002) | (0.002) |
| Number of Family Members | | | 0.001 |
| | | | (.002) |
| n-1 | 85,330 | 85,329 | 85,328 |
| Adjusted $R^2$ | 0.003 | 0.016 | 0.02 |

Notes: Standard errors are shown in parenthesis. The *** indicates that the estimate was statistically significant at 99% confidence level and ** at 95% confidence level.
Source: Author's calculation based on the Department of Education (2020)

Table 5. Results from Duration Model Regression Analysis–Days to Dropout

| | 2018 Cohorts<br>Dependent variable: days to drop out | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2018 Eighth Grade Cohort | | | | 2018 10th Grade Cohort | | | |
| | Cox Proportional Hazards Regression | | Parametric Regression (Weibull Distribution) | | Cox Proportional Hazards Regression | | Parametric Regression (Weibull Distribution) | |
| Covariates | Hazard Ratio | p-value | Hazard Ratio | p-value | Hazard Ratio | p-value | Hazard Ratio | p-value |
| María High Impact Group | 0.945 | 0.625 | 0.944 | 0.621 | 0.635** | 0.000 | 0.633** | 0.000 |
| María Medium Impact Group | 1.184** | 0.031 | 1.181** | 0.034 | 0.919 | 0.254 | 0.918 | 0.248 |
| HH Income below Poverty Threshold | 1.445** | 0.000 | 1.439** | 0.000 | 1.790** | 0.000 | 1.795** | 0.000 |
| Presence of Disability | 0.720** | 0.000 | 0.722** | 0.000 | 0.860* | 0.052 | 0.859* | 0.052 |
| 7th grade Meta Score | 0.468** | 0.000 | 0.472** | 0.000 | | | | |
| 8th grade Meta Score | | | | | 0.470** | 0.000 | 0.468** | 0.000 |
| Female | 0.710** | 0.000 | 0.713** | 0.000 | 0.778** | 0.000 | 0.777** | 0.000 |
| Non-Puerto Rican | 1.940** | 0.002 | 1.951** | 0.002 | 1.060 | 0.817 | 1.062 | 0.811 |
| Rural | 0.861* | 0.072 | 0.860* | 0.070 | 0.776** | 0.004 | 0.777** | 0.004 |
| School Poverty Headcount | 3.397** | 0.022 | 3.443** | 0.020 | 1.999** | 0.044 | 2.009** | 0.043 |
| Global Test for Proportional-Hazards Assumptions $Chi^2$ | 59.75 | 0.000** | | | 23.660 | 0.002** | | |
| | 2020 Cohorts | | | | | | | |
| | Cox Proportional Hazards Regression | | | | 2020 10th Grade Cohort | | | |
| | Cox Proportional Hazards Regression | | Parametric Regression (Weibull Distribution) | | Cox Proportional Hazards Regression | | Parametric Regression (Weibull Distribution) | |
| Covariates | Hazard Ratio | p-value | Hazard Ratio | p-value | Hazard Ratio | p-value | Hazard Ratio | p-value |
| Earthquake High Impact Group | 2.105** | 0.044 | 2.107** | 0.044 | 0.719 | 0.338 | 0.720 | 0.339 |
| Earthquake Medium Impact Group | 1.047 | 0.790 | 1.048 | 0.787 | 1.220** | 0.031 | 1.220** | 0.031 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| HH Income below Poverty Threshold | 1.105 | 0.662 | 1.106 | 0.660 | 1.471** | 0.003 | 1.470** | 0.003 |
| Presence of Disability | 1.020 | 0.916 | 1.019 | 0.918 | 0.839* | 0.098 | 0.842 | 0.104 |
| Seventh grade Meta Score | 0.605** | 0.000 | 0.604** | 0.000 | | | | |
| Eighth grade Meta Score | | | | | 0.471** | 0.000 | 0.472** | 0.000 |
| Female | 0.851 | 0.350 | 0.851 | 0.350 | 0.764** | 0.003 | 0.765** | 0.003 |
| Non-Puerto Rican | 1.590 | 0.360 | 1.585 | 0.364 | 0.930 | 0.850 | 0.931 | 0.851 |
| Rural | 0.897 | 0.591 | 0.894 | 0.577 | 1.022 | 0.842 | 1.022 | 0.842 |
| School Poverty Headcount | 8.638* | 0.073 | 8.277* | 0.077 | 3.349* | 0.056 | 3.324** | 0.057 |
| Global Test for Proportional-Hazards Assumptions $Chi^2$ | 12.53 | 0.185 | | | 9.710 | 0.374 | | |

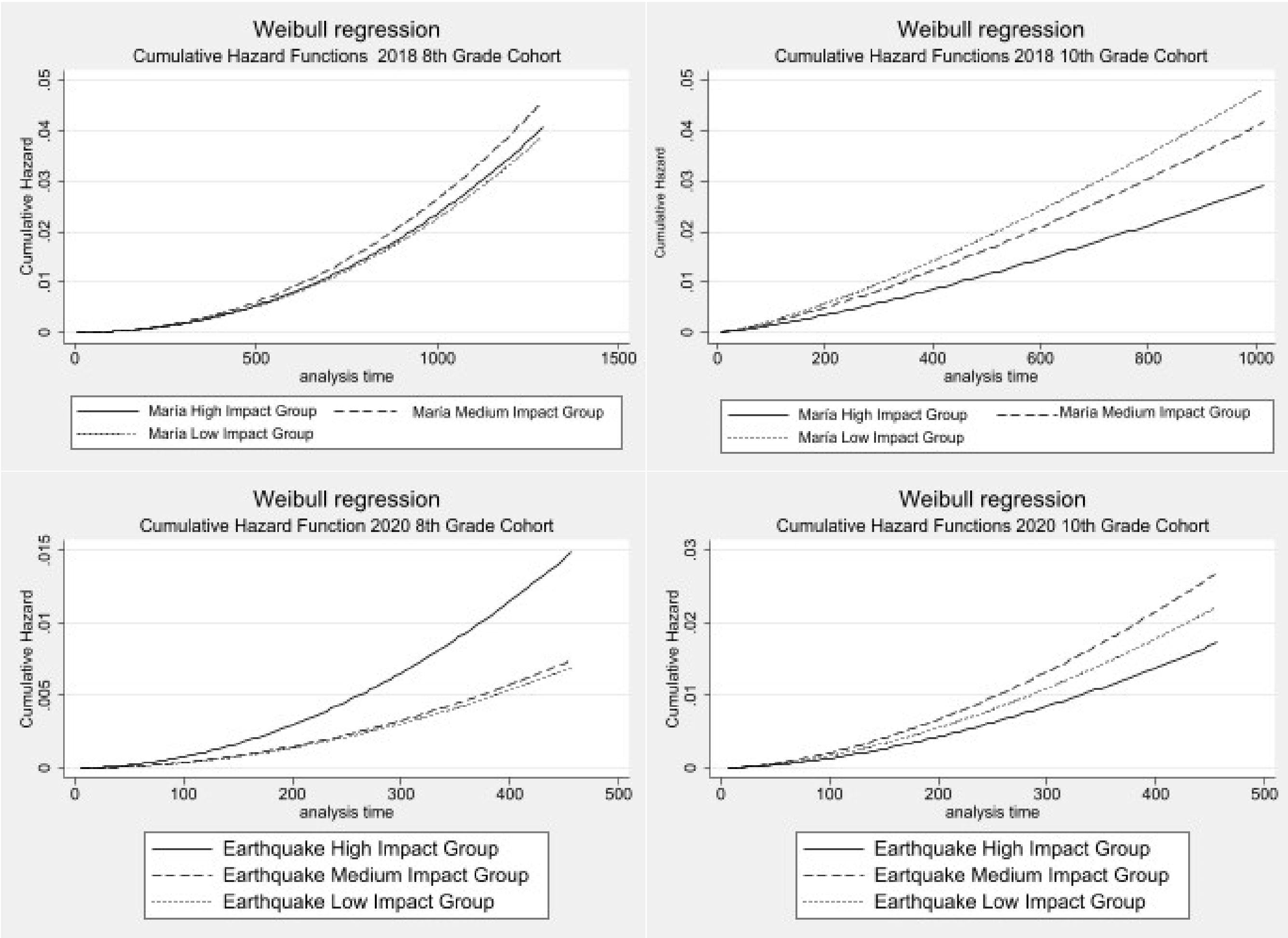
Note: All models presented include school grade indicator variables.

* Significant at a 0.10 level

**Significant at a 0.05 level

Source: Authors' calculations based on the OpenFema Housing Assistance Program Data and the DE (2021)

**Figure 4. Cumulative Hazard Functions by Cohort**




Source: Authors' calculations based on the OpenFema Housing Assistance Program Data and the DE (2021)