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## Disruption to schooling: Evidence from volcano eruptions on Java Island, Indonesia

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## **ADB Working Paper Series**

### **DISRUPTION TO SCHOOLING: EVIDENCE FROM VOLCANO ERUPTIONS ON JAVA ISLAND, INDONESIA**

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**Abstract**

Volcanic eruption is a frequent occurrence in Indonesia, especially on the densely populated Java Island; therefore, policy to improve resilience in children's education is an important avenue. We examine the causal impact of the 2010 Mt. Merapi and 2014 Mt. Kelud eruptions on children's school continuation. We utilize triple difference with continuous treatment estimation and find that a volcanic eruption reduces the likelihood of children being enrolled in school and that the effect can worsen over time. The effect is likely driven by the reallocation of education spending to essential household durables spending to cope with the aftermath of the disaster. Heterogeneity analysis reveals that the impact is more pronounced for girls, oldest children, primary-school-aged children, and children living in poor households. Children experience earlier transitions to the labor force as a consequence of the disruption. To formulate policy recommendations, we conduct a mediation analysis and find that school infrastructure, the pupil-teacher ratio, and telecommunication networks are important factors mediating the volcano eruption's negative impact.

**Keywords:** volcano eruption, school enrollment, education resilience

**JEL Classification:** I21, Q54, J13

# 1 Introduction

Indonesia is situated in the Pacific Ring of Fire and has the largest number of active volcanoes in the world (Siebert, Simkin & Kimberly 2011). This has exposed the country to some of the most destructive volcanic eruptions in the world. Over the last two decades, Indonesia has experienced several volcanic eruptions described as “catastrophic” according to the Volcanic Explosivity Index (VEI) classification (Smithsonian Institution 2023b,c,d)<sup>1</sup>, all of which occurred on Java Island. Java happens to be the most populated island in Indonesia, which increases the possible damage of volcanic activities. Catastrophic volcanic eruptions have long-term impacts since infrastructure reconstruction requires time and households experience income shocks, which may negatively affect children’s education. The adverse impact on children’s education not only affects individuals’ human capital formation but also results in long-term consequences for a country’s poverty alleviation and economic growth.

This study examines the impacts of two catastrophic volcanic eruptions, namely the Mt. Merapi eruption in late 2010 and the Mt. Kelud eruption in early 2014, on children’s school continuation. Adverse events such as natural disasters, specifically volcanic eruptions, may amplify factors driving the decision to drop out of school; many children in Indonesia are already leaving school midway and do not complete the nine years of compulsory education (Ministry of Education and Culture 2019; Suharti 2013). Illuminating how volcanic eruptions disrupt educational activities can provide insight into how to build a more disruption-resilient educational system.

Several studies investigate the impact of natural disasters on the educational outcomes of children<sup>2</sup>, with the most common forms of natural disasters being studied being floods<sup>3</sup>, droughts<sup>4</sup>, storms<sup>5</sup>, earthquakes<sup>6</sup>, and crop loss<sup>7</sup>. Most of the empirical evidence on the impact of natural

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<sup>1</sup>The Volcanic Explosivity Index was developed by Newhall & Self (1982) to measure the “explosive magnitude” of volcanic eruptions. Please refer to their work for more complete elaborations. We provide some explanations on the meaning of the index in section 4.

<sup>2</sup>See Baez, de la Fuente & Santos (2010) for a systematic review on the topic.

<sup>3</sup>See Aguilar & Vicarelli (2011), Caruso (2017), Guin (2015), Nguyen & Minh Pham (2018), and Thamtanajit (2020).

<sup>4</sup>See Nguyen & Minh Pham (2018).

<sup>5</sup>See Baez & Santos (2007), Bustelo (2011), Caruso (2017), Deuchert & Felfe (2015), Eskander & Barbier (2022), Gitter & Barham (2007), Guin (2015), Nguyen & Minh Pham (2018), Sacerdote (2012), and Ureta (2005).

<sup>6</sup>See Bustelo (2011), Caruso (2017), Di Pietro (2018), Hermida (2011), Paudel & Ryu (2018), and Sulistyaningrum (2013, 2017).

<sup>7</sup>See Bandara, Dehejia & Lavie-Rouse (2015), Beegle, Dehejia & Gatti (2006), Cameron & Worswick (2001), De Vrejer, Guilbert & Mesple-Soms (2015), and Jensen (2000).

disasters on educational outcomes comes from developed countries, Latin America, or Africa. Meanwhile, research on volcanic eruptions and their impact on children’s education outcomes in Asia, especially in Indonesia, is limited.

Sulistyaningrum (2013, 2017) investigates the impact of earthquakes and floods using an aggregated index of disasters using the difference-in-difference method and the Indonesian Family Life Survey (IFLS) between 2000 and 2007, and she finds a significant negative impact on children’s test scores. Cas et al. (2014) examine the impact of Aceh’s tsunami with a longitudinal survey between 2004 and 2006 of children who live in Aceh and lost their parents in the disaster using two-way fixed effect estimation, and they find lower children’s educational attainment, particularly for girls. Rush (2014, 2018) examines the impact of the natural disaster index from the DesInventar disaster database on the regional average of children’s school enrollment in either primary or lower secondary school from the Statistics of Indonesia using a two-way fixed effect. These studies find that natural disasters between 2002 and 2010 negatively influenced children’s school enrollment. Accordingly, there is not yet a study on how volcanic eruptions wreak havoc on the educational system in Indonesia.

The volcanoes in our study, Mt. Merapi and Mt. Kelud, spewed ash and heat clouds for more than 2 weeks that reached more than 120 km from the peak. Unlike other disasters (with drought as an exception), volcanic activities can last for an extended period, even up to a month in our context. Furthermore, numerous social and economic activities were halted during the extended eruption period, as well as the aftermath. School closures and evacuee displacement made readjustment to pre-eruption daily life increasingly arduous (Mei et al. 2013, 2016; Sulistiyanto 2013; Warsini et al. 2014, 2015).

We investigate the impact of the Mt. Merapi and Mt. Kelud eruptions on children’s schooling continuation between 2007 and 2014 using the IFLS longitudinal survey and the geo-distance of subdistricts. We look at the triple difference of the time period, treatment status, and distance to the volcanoes. The first difference is the time before and after the eruption. The second difference is between people living near the volcanoes that erupted (Mt. Merapi and Mt. Kelud) and those who live near other similar volcanoes that did not erupt during our study period. The final difference is the distance between the peaks of the volcanoes and the subdistrict (central point) where people live. Our main estimation limits the sample to within a 120-kilometer radius following reports about

Mt. Merapi’s eruption radius, which is smaller than that of Mt. Kelud, which spewed ashes to 500 km away.

We find statistically significant evidence that volcano eruption on average decreases the likelihood of children being enrolled in school, especially for Mt. Merapi due to its longer eruption duration. We show using event study analysis that the parallel trend assumption holds, which indicates that there are no time-variant differences before the eruption between the treatment and control groups. Our result still holds after employing matching methods to construct samples with the same baseline characteristics while including individual fixed effects in our estimation. We find that only a small number of people migrated from the affected region during the eruption, either temporarily or permanently. Based on this, we further argue that the selection bias of people living in the volcano radius and migrating due to the eruption is minimal.

We find that the negative impact on school continuation grows over time, illustrating the persistent effect of the volcano eruption. The mechanism analysis reveals that the effect is driven by the reduction in education spending and the reallocation to durable goods and household furniture spending to cope with the effects of the disaster. Children affected by the eruption are more likely to drop out, enter the labor market when they are school age, and have a lower cognitive test score, especially after 3 years and when the eruption happened when children were at a young age. Analyzing heterogeneity in the treatment effect, we find that the adverse impact is more pronounced for girls, oldest children, primary schoolers, and children living in poor households. Our mediation analysis suggests the importance of school availability, improvement in the teacher-student ratio, and good telecommunication networks as factors that can mediate the negative shock.

The remainder of the paper will proceed as follows. In section 2, we review the context of eruptions and education in Indonesia. In section 3, we elaborate on the data and sample construction. In section 4, we describe our empirical strategy to identify the causal impact. We then present our results, robustness checks, and heterogeneity analysis in section 5. Finally, section 6 discusses the implications of our results and section 7 concludes the paper.

## 2 Volcano and Education in Java

### 2.1 Mt. Merapi and Mt. Kelud eruptions

The eruption of the Toba Caldera 74,000 years ago, Mt. Tambora in 1815, and Mt. Krakatoa in 1883 have made Indonesia the home of some of the most colossal volcanic eruptions in the history of mankind (Siebert, Simkin & Kimberly 2011). The Sunda Arc, which spans from Sumatra Island to Flores Island, hosts the majority of Indonesian volcanoes (Pacey, Macpherson & McCaffrey 2013). It is within this line that the densely populated island of Java sits.

The 2010 Mt. Merapi eruption was one of the most catastrophic eruptions in Indonesia (Smithsonian Institution 2023c). The socioeconomic impact of the Merapi eruption has been substantial since Mt. Merapi is “one of the most densely populated volcanoes in the world” (Mei et al. 2016). Throughout the eruption period, which started in late October 2010 and lasted for a little over a month, the volcano continued to distribute volcanic ash and heat clouds that extended over vast areas. Schools as far as 120 km from Yogyakarta, where Mt. Merapi is located, were closed for the entire duration of the eruption (Widhiarto 2010).

Mt. Kelud is located in the Kediri District, East Java Province. It started to erupt in mid-February 2014 for a week, a much shorter duration than the Merapi eruption. However, the burst of volcanic ash covered further distances, as far as 500 km from the mountain (Natallova 2014). The eruption practically paralyzed major parts of East and Central Java (The Jakarta Post 2014). However, the eastern regions of East Java were not affected by the Mt. Kelud eruption. Apparently, volcanic ash moved only to the west, south, and north of the volcano (JPNN 2014; Nurgomar 2014).<sup>8</sup>

During the last five decades, Java Island has experienced several major volcanic eruptions (Smithsonian Institution 2023a). Mt. Raung, which is located on the eastern side of the province of East Java, erupted five times between 1982 and 1997, with the most recent eruption in June 1997, when ash was observed at heights of 5 km above the volcano. Mt. Galunggung most recently erupted in 1982, during which the ash disrupted flights in Singapore and Malaysia. During the study period between 2007 and 2014, Mt. Bromo erupted in 2010, but we excluded the sample of Mt. Bromo from our treatment and control groups because the VEI was below 4 (*ibid.*).

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<sup>8</sup>This helps our identification strategy, as the treatment units in Mt. Kelud’s radius do not intersect the control units in Mt. Raung’s radius.



## 2.2 Education in Indonesia

Since 1994, nine years of schooling have been compulsory in Indonesia. This consists of six years of primary schooling (SD/Sekolah Dasar) and three years of junior secondary schooling (SMP/Sekolah Menengah Pertama). Recently, the government and parliament have been discussing raising the amount of compulsory schooling to 13 years. This new proposal would require an additional year of preschool and three years of senior secondary schooling (SMA/Sekolah Menengah Atas). However, 20 years after the enactment of the 1994 policy, enrollment in junior secondary and senior secondary schooling is nowhere near universal (Suharti 2013).

Primary school is typically the starting point of an Indonesian child’s long educational journey because many families do not enroll their children in any type of preschool, as evidenced by its low enrollment rate (Alatas et al. 2013; Ministry of Education and Culture 2019). Since 2003, parents have been able to choose to enroll their children in primary school as early as age six. However, the official start of compulsory schooling is still age seven. Children who have turned seven are obliged to enroll in primary school in the closest upcoming academic year. The 2003 law also requires public schools, which are available in more abundance than private schools due to the 1970s primary school construction program (Duflo 2001; Suharti 2013), to prioritize the enrollment of seven-year-old children rather than younger children. Nonetheless, some children still enroll at a younger age, a pattern more commonly observed in private schools. In any case, with six years of education, most primary school students, assuming no grade repetitions, graduate at around age 12.

After primary school, children proceed to study in junior secondary school and then senior secondary school, each of which takes three years to complete. The most common age range is 13–15 years old for junior secondary school and 16–18 years old for senior secondary school. However, as in primary school, there are cases of early enrollments and late graduations, which could be due to grade repetitions or special acceleration classes in which students can complete their education in two instead of three years.

This phase of education varies due to many conjunctures as children become part of the adolescent and working-age populations, typically in the last year of junior secondary school. The risk of dropping out of school and early entry into the labor force is heightened in this phase of school-

ing. Due to the economy’s substantial and ever-expanding informal sector, many informal jobs in Indonesia require only a high school diploma (ADB & BPS 2011; Cuevas et al. 2009; Rothenberg et al. 2016). Furthermore, Suharti (2013) shows that the availability of public schools at the junior or senior high school level is lower than that of private schools. This could potentially discourage households from enrolling their teenage children in secondary schools, as private schools are more expensive on average.

### 3 Data and Sample Construction

#### 3.1 Data

We draw our main dataset from the Indonesia Family Life Survey (IFLS). The IFLS is a rich dataset containing various information on community, household, and individual characteristics. It is also the only longitudinal survey in Indonesia made available to the public. The IFLS launched its first wave in 1993, covering 7,224 households from 13 provinces, representing 83% of Indonesia’s population at the time. Afterward, the IFLS was conducted in 1997, 2000, 2007, and 2014, tracking the household members of the 1993-wave households. In this study, we utilize data from Wave 4 (2007) and Wave 5 (2014).

The IFLS asked education history questions, including the year of enrollment and education outcomes for every individual in the panel dataset; thereby, we are able to observe children’s education history between 2007 and 2014. In addition, the IFLS also has a work and migration history module that allows us to map out the working history and geographical mobility of the sample annually between 2007 and 2014.

To identify observations within the volcanoes’ area of impact, we use information on the latitude, longitude, and distance between the peaks of the volcanoes and the subdistrict’s central point (subdistrict office) from Google Maps. We then use the IFLS subdistrict code to match the Google Maps database.<sup>9</sup> To examine the available public infrastructure in the regions, we use the IFLS community dataset and Potensi Desa (Village Potential/PODES), a government-led census of all villages in Indonesia. Both the PODES and IFLS community datasets contain information about schools and infrastructure related to children’s schooling that we use to examine the mechanism

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<sup>9</sup>The subdistrict level is the lowest geographical identifier in the IFLS data.

and mediation factors underlying the eruption effect. We match the dataset to the community ID for the IFLS community database. For PODES, we aggregated the data at one level higher, from village to subdistrict, to match it with the IFLS and geo-distance dataset.

We also utilize SUSENAS, a government-led household survey, to calculate the population of school-age children in each district for the mediation analysis. Following Federman & Levine (2005), we use Statistik Industri Pengolahan (Manufacturing Industry Statistics) to obtain the growth of employment in the manufacturing industry at the district level. This serves as a proxy of industrialization in the region, which may influence the opportunity costs of schooling. Lastly, we make use of the Centre of Humanitarian Data’s subnational shapefiles to calculate the area size of each subdistrict.

### 3.2 Sample construction

Our study leverages the Mt. Merapi and Mt. Kelud eruptions as exogenous shocks, and we choose Mt. Galunggung in West Java and Mt. Raung in East Java as the control volcanoes. Both Mt. Galunggung and Mt. Raung are selected because these volcanoes are also located in Java and have a history of eruptions with a VEI of at least 3; hence, we could reduce the bias from unobserved sociocultural and geographical differences within the island. In addition to the four volcanoes that we have mentioned, Mt. Semeru and Mt. Bromo have also experienced eruptions with a VEI of at least 3 (Smithsonian Institution 2023a). However, only Galunggung and Raung can be used as controls since both are not in the catchment areas of Mt. Merapi and Mt. Kelud.<sup>10</sup>

We apply several criteria to construct our sample. First, our treatment and control samples must be school-age children, which means they must be 6–19 years old between 2007 and 2014. Second, since we are interested in studying school continuation against adverse shocks, our sample

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<sup>10</sup>Both Semeru and Bromo are within Kelud’s catchment area. There are some important additional notes about the treatment-control assignment. First, some regions are within the catchment areas of both Kelud and Raung, namely the districts Lumajang and Probolinggo. Yet, as explained in section 2, these areas lie east of Mt. Kelud and were not affected by the Kelud eruption. Therefore, we put these areas into the control group. Second, some samples are also located within the Kelud catchment area but were not affected by the Kelud eruption and are not within the Raung catchment area either. This area is the Pasuruan District. We re-categorize the treatment status of samples in this district as missing. Third, there is also some overlap of the catchment areas of Merapi and Kelud. The number is minuscule (13 observations). These samples are located in the districts Magetan, Ngawi, and Ponorogo, which lies on the border of Central and East Java. Considering that the Merapi eruption struck first, these units would have been treated if they had been used as treatment units in the Kelud estimation sample. As such, we use these units as Merapi treatment units and drop them from the Kelud sample set. Consequently, the treatment units in Kelud consist of children who have never been exposed to volcanic eruptions.

must be enrolled in school, either primary or secondary school, at the time of the volcano eruption. For the Merapi estimation sample, our sample must be enrolled in school in the academic year 2010/2011, and the Kelud sample must be enrolled in the academic year 2013/2014<sup>11</sup>. The control group follows the enrollment rule for the treatment sample. The control group for the Mt. Merapi sample is children living in the catchment of Mt. Raung and Mt. Galunggung and enrolled in the 2010/2011 academic year, while the control for the Mt. Kelud sample is children living in the catchment of Mt. Raung and Mt. Galunggung and enrolled in the 2013/2014 academic year. Note that we focus our research on the impact on public, private, vocational, and religion-based schools, which account for the majority of students in Indonesia, and we exclude schools for persons with disabilities (SLB) and adult education (Kejar Paket). Applying these filters gives us 13,565 children aged 6–19 years old across two waves for the Merapi estimation sample (including the treatment and control groups) and 14,105 children for the Kelud estimation sample.

Third, our sample must live in subdistricts located within a maximum radius of 120 km from the treatment volcanoes (Mt. Merapi and Mt. Kelud) and selected control volcanoes (Mt. Galunggung in West Java and Mt. Raung in East Java).<sup>12</sup> We chose 120 km as the maximum catchment distance because it was the reported 2010 Merapi eruption ashfall radius and smaller than Mt. Kelud’s eruption radius, as elaborated in section 2.<sup>13</sup> Restricting the sample to this criterion results in 3,649 samples for the Merapi estimation and 3,097 samples for the Kelud estimation across two waves. Finally, children in our sample must appear in both waves because we are measuring school continuation as our main outcome. Thus, our final sample size is 2,648 for the Merapi estimation and 1,888 for the Kelud estimation across two waves. Table 1 provides the sample allocation between the treatment and control groups in both sample sets across two years.<sup>14</sup>

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<sup>11</sup>The Mt. Merapi eruption happened at the end of 2010; therefore, we use the 2010/2011 academic year. Meanwhile, Mt. Kelud erupted at the beginning of 2014, so we use the 2013/2014 academic year

<sup>12</sup>Note that since the subdistrict is the lowest level of location identifier available in the IFLS data, all children in each subdistrict will have one value for distance. Hence, if the subdistrict has a distance  $\leq 120$  km, all children in the subdistrict will be included in the sample (whether they are in treatment or control depends on whether they are in the catchment areas of the treatment or control volcanoes). Understandably, there is a gap in precision in our sample construction, as a child’s house might be located more than 120 km away from the selected volcanoes, yet they will nonetheless be included in the sample because the subdistrict’s central point is within the catchment area of the volcano. This risk is amplified in larger subdistricts. To ensure that the errors are distributed evenly across treatment and control groups, we test for the balance of the subdistrict area size and children population density between treatment and control subdistricts in Appendix B. We find that the size of the subdistrict and children population density in the treatment and control groups are balanced.

<sup>13</sup>The 120 km radius criterion is for our main estimation. However, we also conduct a robustness check by restricting the sample to various shorter distances from the peak to examine the differences in the impact.

<sup>14</sup>The effective number of observations used in the estimation slightly drops again due to missing values in some

Table 1: Sample size

	Merapi estimation	Kelud estimation
Control	1,333	1,166
Treatment	1,315	722
Total	2,648	1,888

Source: Authors' calculation

### 3.3 Summary statistics

Table 2 provides the summary statistics of the individual, parental, household, and area characteristics of our sample at the baseline (2007). Children in our treatment group who are living in the Mt. Merapi and Mt. Kelud catchment areas have a similar gender ratio and ages to the control group. The children are almost nine years old on average in 2007.

The fathers of these children on average have eight to nine years of schooling and are 39 years old, and nearly 98% are Muslim. In terms of occupation, the share of government workers is very small, at around 4–8%. A large share of fathers are either self-employed or workers in the private sector. These fathers' characteristics do not seem to differ widely between the treatment and control groups. Like the fathers, the mothers in our treatment group have similar characteristics to control mothers in terms of age, religion, year of schooling, and occupation.

Almost 90% of our study sample lives in a male-headed household. The control group has more children living in urban areas and has a slightly larger household size compared to the treatment groups. As part of our matching exercise, we conduct a simple t-test as a formal way to verify baseline covariate imbalance. We include the results in the complete propensity score matching (PSM) tabulation results in Appendix C (Table A7 for the Merapi sample and Table A8 for the Kelud sample). As the table shows, there are covariate imbalances at the baseline. However, the identifying assumption of our empirical strategy using difference-in-difference (DiD) does not require balance at the baseline. For the parallel trend assumption to hold, we need only provide evidence that the covariate imbalance is constant over time (Gertler et al. 2010; Khandker, B. Koolwal & Samad 2009). As we will show later in subsection 5.3, this is certainly the case in our study.

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of the covariates, but the drop is negligible.

Table 2: Summary statistics of Baseline period

	Mt. Merapi mean	Mt. Kelud mean	Control mean
Child is male	0.50	0.48	0.52
Age of children	8.88	8.48	8.29
Living in urban area	0.53	0.49	0.60
Household size	9.05	8.94	9.07
Male household head	0.88	0.89	0.86
Father's years of schooling	8.66	8.47	7.85
Father's age	38.95	39.00	38.83
Father is Muslim	0.95	0.98	0.92
Father is self-employed	0.41	0.34	0.28
Father is government worker	0.08	0.04	0.08
Father is private worker	0.25	0.33	0.27
Father is casual worker	0.09	0.12	0.12
Father is not working / unpaid worker	0.15	0.17	0.21
Mother's years of schooling	8.61	8.22	7.45
Mother's age	36.90	35.86	36.01
Mother is Muslim	0.95	0.98	0.92
Mother is self-employed	0.23	0.18	0.18
Mother is government worker	0.06	0.03	0.04
Mother is private worker	0.13	0.17	0.15
Mother is casual worker	0.05	0.07	0.05
Mother is not working / unpaid worker	0.52	0.55	0.58
Growth of industry employment in district	0.00	0.05	0.04
Have public electricity access	0.98	1.00	0.99

Source: Authors' calculation

## 4 Empirical Design

### 4.1 Estimation method

Our primary estimation method is two-period triple differences between the time period, treatment status, and distance from the volcanoes' peaks to the subdistricts' central points (defined as the subdistrict office) as a continuous treatment variable. We use the 2007 wave / IFLS4 as the pre-treatment period and the 2014 wave / IFLS5 as the post-treatment period. The estimation strategy enables us to examine the average treatment effect of volcanic eruption since we include the distance variable in the interaction term to take into account any heterogeneous effect of the geographic location of the children's living area. The triple difference coefficient shows that within the affected area (that is, 120 km radius), volcanic eruption reduces the likelihood of children being in school by  $100 \cdot \beta_1$  percentage points per 100 km. This number represents the intensity of the impact. The distance to the volcano could be a confounding factor in children's school enrollment decisions and

households can migrate during the study period. Therefore, including the distance in our triple difference estimation isolates its confounding effect and makes the treatment effect purely represent the response to the volcanic eruption.

We also use individual fixed effects  $\tau_i$  to remove bias from time-invariant unobserved differences between the treatment and control groups, which may be correlated with both the outcome and the likelihood of being disrupted by the eruption. Our main estimation is given by equation 1:

$$y_{ist} = \alpha_0 + \alpha_1 Treat_{is}.Post_t.Distance_{ist} + \alpha_2 Treat_{is}.Post_t + \alpha_3 Post_t.Distance_{ist} + \alpha_4 Treat_{is}.Distance_{ist} + Treat_{is} + Post_t + Distance_{ist} + \alpha_5 X_{ist} + \alpha_6 Latitude_s + \alpha_7 Longitude_s + \tau_i + \epsilon_{ist}, \quad (1)$$

where  $y_{it}$  is the children’s outcomes,  $Treat_{is}$  is whether child  $i$  living in subdistrict  $s$  is affected by the eruption,  $Post_t$  is a time dummy variable for the post-eruption period, and  $Distance_{ist}$  is the distance to the volcano of child  $i$  living in subdistrict  $s$  at time  $t = \{2007, 2014\}$ . By controlling the individual’s, parent’s, household’s, and area’s characteristics ( $X_{ist}$ ), and including the time-fixed effect  $Post_t$ , we can control for possible time-variant confounders, which can bias the treatment effect of the volcano eruption ( $\alpha_1$ ). All estimations use the district-level cluster standard error, except for the stacked sample estimation. Following Cengiz et al. (2019), the never-treated group appears twice in the stacked estimation; therefore, we cluster standard errors at the sample group-district level. Furthermore, due to the sample size limitation of the treatment group, we estimate all the regressions using bootstrap simulation to obtain more precise standard errors.

## 4.2 Robustness tests and sensitivity analysis

We also use an event study design to investigate the year-by-year dynamics of the volcano eruptions and to test for parallel trend assumptions, with the same triple difference with continuous treatment approach. By expanding the dataset to eight years (2007–2014), the event study design allows us to examine the parallel trends in outcomes between the treated and control groups in the absence of treatment. In the context of our study, there might be a threat of the violation of the parallel trend assumption given that severe or large eruptions<sup>15</sup> in our control volcanoes occurred before the

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<sup>15</sup>Newhall & Self (1982) define a “severe” or “large” eruption as an eruption with a VEI of at least 3. A VEI of 2 represents a “moderate” eruption and a VEI of 4 is “catastrophic,” such as in the case of the Merapi and Kelud

2000s (Smithsonian Institution 2023a).

Specifically, the covariates in the event study analysis are the children’s age, parent’s age, parents’ job status from the work history module, and latitude and longitude from the matching of the migration history and Google Maps database.<sup>16</sup> We complement this with province-time fixed effects to take into account time-variant province-level differences.<sup>17</sup> We use the following estimation for the event study:

$$\begin{aligned}
y_{ist} = & \beta_0 + \beta_1 Distance_{ist} + \beta_2 Latitude_s + \beta_3 Longitude_s + \beta_4 Z_{ist} + \beta_5 RelativeTime_t \\
& + \beta_6 Treat_{is} Distance_{ist} + \beta_\tau \sum_{\tau=-1}^{-1} RelativeTime_\tau Treat_{is} Distance_{ist} \\
& + \beta_T \sum_{T=0}^4 RelativeTime_T Treat_{is} Distance_{isT} + \tau_i + \epsilon_{ist}. \quad (2)
\end{aligned}$$

In addition to testing the validity of the identifying assumption, we run more robustness checks using the two-period setup to test the sensitivity of our results. First, to examine if there is heterogeneity of impacts at various distances to the volcano, we shorten the radius of the catchment to 100, 80, and 60 km. Second, we also test if our results are sensitive to covariate inclusion by stripping the covariates out of the estimation. Third, we test if the results persist under alternative specifications with different covariates. Finally, to address potential issues of selection bias in the selection of people who live on the treatment volcanoes and control volcanoes<sup>18</sup>, we use the 2007 wave to construct the sample with two different matching techniques, propensity score matching and entropy balancing. We then apply the triple difference with continuous treatment estimation strategy to the matched sample and obtain similar results. We also examine the migration history

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eruptions. The last time our control volcanoes had an eruption with a VEI of at least 3 was 1982 for both Galunggung (VEI of 4) and Raung (VEI of 3).

<sup>16</sup>We are only able to utilize several variables in the event study estimation since the IFLS has limited variables with annual data. We still include age in the estimation because IFLS4 and IFLS5 were conducted at different times of the year, and as a result the individual fixed effect  $\tau_i$  and time fixed effect  $RelativeTime_t$  alone could not absorb the variation. The two-period setup remains our preferred estimation, and we mainly employ this event study design to provide an indication of whether the parallel trend assumption holds.

<sup>17</sup>We could not include the district-time fixed effect, as the number of fixed effect groups is similar to the subdistrict-time fixed effect, which happens to be our treatment level.

<sup>18</sup>There are indeed differences in characteristics between the treatment and control groups before matching. However, matching and including individual fixed effects can mitigate the potential bias. See subsection 5.2 for a discussion of selection bias.



and find a negligible migration rate in the sample.

## 5 Results

### 5.1 Main results

The effect of a volcanic eruption on children’s schooling is negative and more severe for children living in Mt. Merapi’s catchment area. Table 3 presents the impacts separately for each treatment volcano (columns 1 and 2) and then the stacked sample (column 3). The stacked estimation shows that volcanic eruption reduces the likelihood of being enrolled in school by 8.1 percentage points<sup>19</sup>; this is significant at the 5% level. We only find significant treatment effects of the Mt. Merapi eruption, as it reduces the likelihood of being enrolled in school by 13.3 percentage points (column 1). Meanwhile, we do not find a statistically significant impact of Mt. Kelud’s eruption (column 2). We then restrict the sample to a smaller radius to investigate if any impact of Mt. Kelud’s eruption is present at a shorter distance from the volcano.

Table 3: Main estimation

	Dep. variable: School enrollment		
	Mt. Merapi (1)	Mt. Kelud (2)	Stacked (3)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.0020683*** (0.000803)	0.0000776 (0.0004503)	-0.0011985** (0.000554)
Child’s covariates	✓	✓	✓
Parent’s covariates	✓	✓	✓
Area’s covariates	✓	✓	✓
Subdistrict’s latitude and longitude	✓	✓	✓
Time fixed effect	✓	✓	✓
Individual fixed effect	✓	✓	✓
Obs.	2,325	1,662	3,987
Adj. R2	0.0531	0.0839	0.0682

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: Authors’ calculation

We conduct an estimation of the Merapi and Kelud treatment effects under 100, 80, and 60 km radii. Limiting the sample radius from the peak of Mt. Kelud to 100 km, 80 km, and 60 km changes

<sup>19</sup>The treatment effect is calculated by multiplying the coefficient estimate with the average distance of the children’s subdistrict to the peaks of volcanoes. The average distance for all samples is 67 km, and for the Merapi sample, it is 64 km.

the coefficient from positive to negative. We present this result in Appendix [A.2](#). This suggests that the Mt. Kelud eruption negatively affects schooling outcomes for children living closer to the peak, as indicated by the larger negative treatment effect in the Mt. Kelud estimation. However, we do not find a statistically significant impact of the Kelud eruption on school enrollment under any impact radius. This could be due to the lower sample size, which affects the standard errors.

One might argue that the children living within the catchment area of Mt. Merapi were impacted by the Kelud eruption in 2014, as Kelud’s ashfall went as far as 500 km to the west (Natallova [2014](#)); hence, the proper treatment group for the Kelud impact estimation should also consist of samples in the Merapi catchment area. This assertion has merit, and the fact that the treatment effect of the Merapi eruption is larger than the stacked estimation might have something to do with this. As such, we test this assertion by including samples in the Merapi catchment area in the Kelud estimation sample as treatment units. We present the results of this estimation in Appendix [A.1](#), and we still do not find any impact of the Kelud eruption, which corroborates our main findings.

Our result is also robust to various sensitivity tests. We conduct sensitivity tests along two dimensions. First, we test whether our result is sensitive to covariate inclusion. We find that the result is robust under the covariate inclusion test (Appendix [A.3](#)). We first ran the estimation without covariates and individual fixed effects. We find that the impact is negative but slightly smaller (column 1). Then, we add the covariates (column 2) and individual fixed effects (column 3). We also add precipitation to examine if weather is a confounding factor affecting the disaster severity and impact on children’s schooling (column 4). The result is consistent across specifications, as the treatment effect remains negative and statistically significant.

Second, we test whether our result holds with different covariates. We also find that the result is consistent with alternative covariates (Appendix [A.4](#)). Column 1 is the original specification. We then change the proxy for resource competition within the household from the household size to the number of dependents and school-age children (column 2) and the residence characteristics from electricity usage to whether the house is made of masonry (column 3). We find that the treatment effect stays negative and statistically significant for any specifications. The magnitude of the treatment effect is also similar across specifications.

## 5.2 Addressing threats to identification

### 5.2.1 Migration

One concern with our result is that the volcano eruption could motivate residents to move to another region. If this is the case, there might be potential selection bias in our estimates since decisions around migration might be non-random and confounding factors that affect enrollment decisions. To examine this concern, we use the migration history information in IFLS5, where we found only 10 children who migrated after the November 2010 Mt. Merapi eruption, out of 1,252 children in the Merapi sample (or lower than 1%).<sup>20</sup>

This number is supported by abundant literature in the fields of anthropology, geography, and disasters, which suggests that post-disaster migration is not a common phenomenon in Indonesia. Muir et al. (2019) note that Mt. Merapi remains a densely populated area despite recurring eruptions, and households tend to return to their original location once the situation has stabilized (Amin, Sukamdi & Rijanta 2018; Rahman, Nurhasanah & Nugroho 2016). This is also the case for Mt. Semeru, a volcano near Mt. Kelud (Thouret et al. 2022), as well as other disaster-prone areas due to local culture ties, proximity to economic opportunities, and access to social capital. People tend to have a preference to stay put rather than move somewhere safer (Amin, Sukamdi & Rijanta 2021; Bohra-Mishra, Oppenheimer & Hsiang 2014; Buchori et al. 2018; Goldbach 2017; Langlois et al. 2023).

Muir et al. (2020) find that households that have been given an incentive to relocate after disaster remain reluctant to do so. Sulistiyanto (2013) also notes how local communities around Mt. Merapi pressured the government to not simply resort to moving victims to other islands, a common disaster relief approach in the past. In line with this, Mei et al. (2016) document how the resettlement program for victims of the 2010 Merapi eruption outside of their original residential location was challenging.

The resistance to post-disaster migration is not a pattern exclusive to Java and can be found in other regions affected by disaster; for example, this pattern occurred for the 2004 Aceh tsunami and 2005 Nias earthquake in Indonesia (Brata, de Groot & Rietveld 2014), Tropical Storm Stan in

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<sup>20</sup>We can only analyze the post-eruption migration pattern in the Merapi sample since Mt. Kelud erupted during the endline year. However, Mt. Kelud's eruption was less destructive than that of Mt. Merapi; therefore, we assert that the migration rate is smaller compared to Mt. Merapi.

Guatemala in 2005 (Bustelo 2011), the 1999 earthquake in Colombia (Bustelo, Arends-Kuenning & Lucchetti 2012), and the 1987–1989 locust plague in Mali (De Vreyer, Guilbert & Mesple-Soms 2015). Similar to Indonesia, most post-disaster migration still happens within the boundary of a district or province and most migrants tend to return to their original location shortly after (Restrepo 2000).<sup>21</sup>

As for the within-panel migration, we identify households moving within the treatment group and control group, but we do not identify anyone in our sample who switched from the treatment areas to the control areas or from the control areas to the treatment areas between IFLS4 and IFLS5. This might be due to the large distance between the treatment sample and the control sample. Furthermore, the administrative process to change schools during the academic year when the eruption happened was too cumbersome. Even if any observations moved from treatment to control areas or vice versa, we included controls for the quality of the education system in the area in the subsection on mediating factors (Table 11), following the strategy of De Vreyer, Guilbert & Mesple-Soms (2015). In this exercise, we still find a statistically significant impact of the eruption and an even larger treatment effect magnitude.

### 5.2.2 Dormant control volcanoes

Another threat to our identification strategy is that our control volcanoes have not erupted in a long time. One could argue that Mt. Raung and Mt. Galunggung may have different characteristics from our treatment volcanoes since the last time both volcanoes erupted with a VEI of 3 (severe) or 4 (catastrophic) was 1982. We argue that Java Island is the home of more than half of Indonesia’s population, and the geological landscape is shaped by over 130 volcanoes. People moving from the proximity of one volcano would then live closer to another volcano in Java. Furthermore, each eruption could affect areas with a long-range radius. The ash of the 2014 Mt. Kelud eruption was found on the west side of Java. In addition, it is hard to predict the radius of impact beforehand; hence, pre-disaster migration in anticipation of upcoming danger is as unlikely as post-disaster migration. Moreover, Mt. Raung (our control volcano) erupted after our study period in 2015, 2021,

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<sup>21</sup>Regarding temporary migration during eruptions, we consider the IFLS’ disaster module. Note that the module only asked for a subset of the whole sample, i.e., only those who experienced extreme damage from the disaster. From this limited information, only three households temporarily moved for two days and one household moved for seven days and then returned to their original area, which was affected by the eruption.

and 2022 with a VEI of 2 (explosive) (see Table 4). The sudden increase in Mt. Raung activity shows the unpredictability of the transitions from dormant volcanoes. This further suggests that all Java residents are susceptible to the inherent risk of volcanic eruptions.

Table 4: Volcano eruption timeline

Group	Volcano	Eruption year [VEI]
Treatment	Merapi	1930–1931 [VEI 3], 1961 [VEI 3], 2010 [VEI 4], 2014 [VEI 3], 2018 [VEI 3]
	Kelud	1901 [VEI 3], 1919 [VEI 4], 1951 [VEI 4], 1966 [VEI 4], 1990 [VEI 4], 2014 [VEI 4]
Control	Raung	1953 [VEI 3], 1956 [VEI 3], 1982 [VEI 3]
	Galunggung	1822 [VEI 5], 1894 [VEI 3], 1982–1983 [VEI 4]

Notes. The eruption events are limited to VEIs of 3. All volcanoes in the treatment and control group have erupted several times with lower VEIs. For example, Mt. Galunggung erupted in 1918 and 1984 with a VEI of 1 and Mt. Raung erupted in 1990, 2000, 2002, 2007, 2015, 2021, and 2022 with a VEI of 2.

Source: Eruption history, Smithsonian Institute

### 5.3 Baseline balance and parallel trend

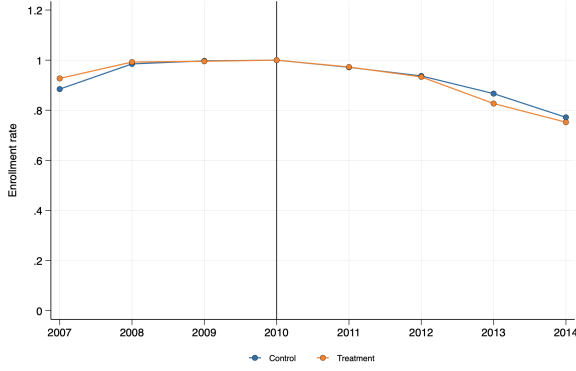
The result is robust in addressing time-invariant selection bias. In the main estimation, we included individual fixed effects to remove any potential time-invariant selection bias.<sup>22</sup> In addition, we apply propensity score matching (PSM) and entropy balancing matching methods to the baseline characteristics before conducting the triple difference estimation. The result is not widely different from the main estimation, indicating that there is no time-invariant selection bias (Appendix D).

The result is also robust in addressing time-variant selection bias. Before we proceeded to formal testing, we plotted the annual aggregate of children’s school enrollment for both samples and found that the trends for children’s school enrollment for the treatment and control groups before the eruptions were moving in tandem. These descriptive statistics provide suggestive evidence that supports our argument for parallel trend assumption (Figure 1). Furthermore, in both cases, the enrollment rate for the treatment groups is lower post-eruption.<sup>23</sup>

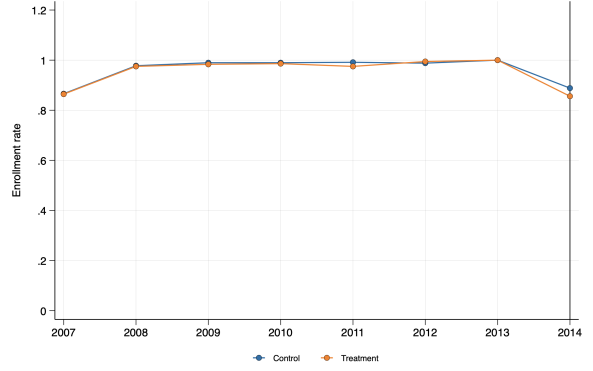
<sup>22</sup>In the robustness checks (Appendix A.3), we also show that removing individual fixed effects does not change the result.

<sup>23</sup>We conduct a t-test for the post-eruption period to examine if there are unconditional differences in school continuation, and we find that the school enrollment of the treatment group is significantly lower at the 5% level for the Mt. Merapi sample and at the 10% level for the Mt. Kelud sample compared to the control group.

Figure 1: Annual school enrollment rate



(a) Mt. Merapi sample

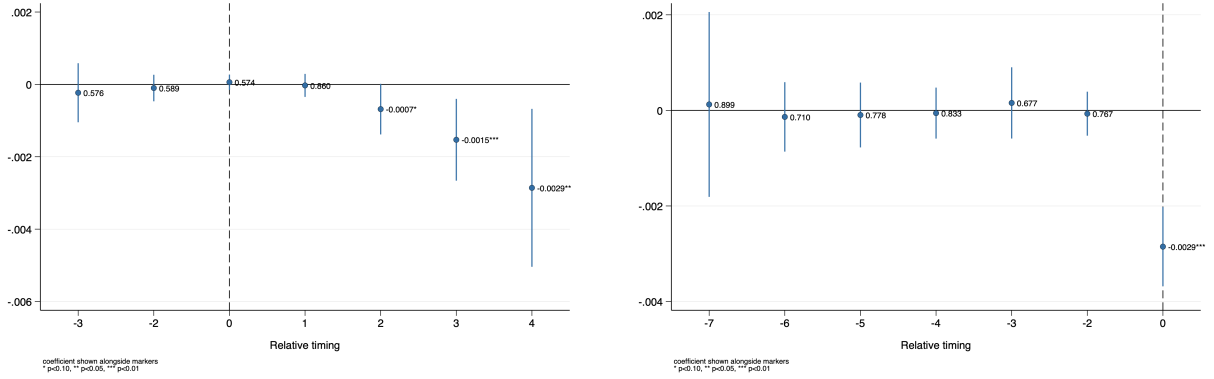


(b) Mt. Kelud sample

Source: Authors' calculation

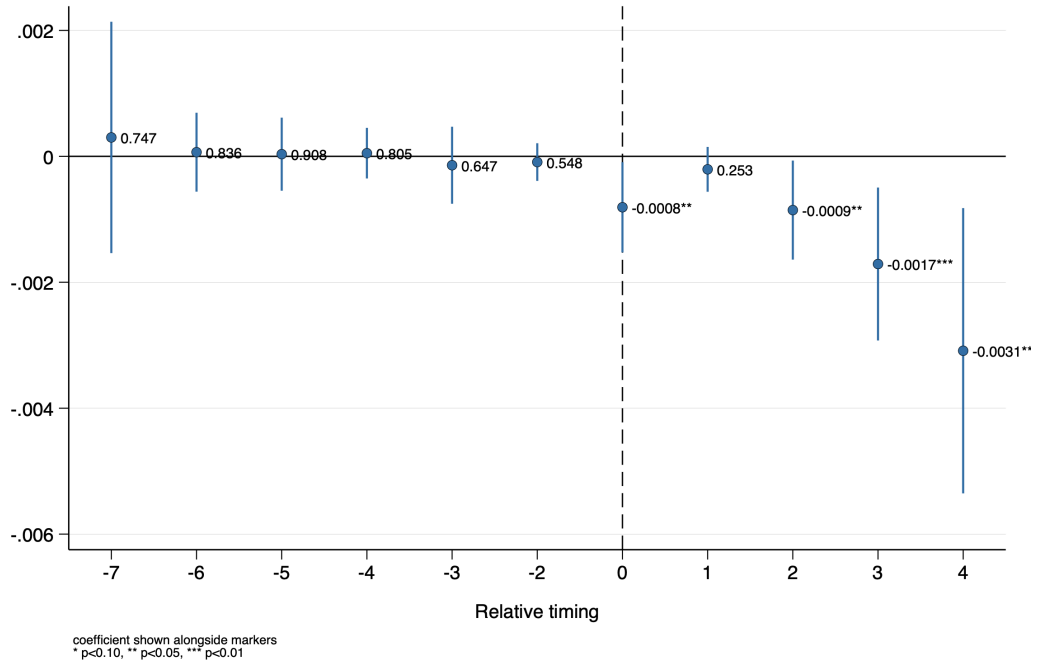
As we have mentioned in the summary statistics (see subsection 3.3), there are baseline imbalances in our sample. However, the parallel trend assumption only requires that the imbalance does not change over time; otherwise, it will confound the treatment effects (Gertler et al. 2010; Khandker, B. Koolwal & Samad 2009). As a formal test, we verify whether the covariate imbalance is constant over time by regressing each covariate on our main estimation (equation 1), as suggested by Wing, Simon & Bello-Gomez (2018). The statistical significance in the triple difference coefficient will tell us whether the covariate imbalance changes over time. We present the results in Table A6 in Appendix C. In the Merapi sample set, only 1 out of the 23 covariates that we employ are imbalanced over time. In the Kelud sample set, only 3 out of 23 covariates are imbalanced over time. As the large majority of the covariates are balanced across time, this is strong support for the parallel trend assumption.

Figure 2: Event study analysis



(a) Mt. Merapi sample

(b) Mt. Kelud sample



(c) Stacked sample

Source: Authors' calculation

Finally, we use an event study identification strategy in equation 2 to examine the parallel trend assumption. This identification strategy has limitations since the IFLS provides incomplete yearly children's and household characteristics. By expanding the data to eight years, we have 18,798 observations spread over 2007–2014, 44.74% of which are treatment units. Figure 2 illustrates the event study results; we found that the pre-treatment coefficients are not different from zero, which supports the parallel trend assumption. As in our main results, the coefficient of interest post-

eruption is negative and statistically significant. In the Mt. Merapi sample, the eruption affected children’s schooling in the second period, while Mt. Kelud’s eruption had an immediate effect. The impact is negative and statistically significant at the 1% level. The stacked and Mt. Merapi results show that the eruption effect grows over the next four years post-disaster.

## 5.4 Mechanism

In this subsection, we explore the possible mechanisms driving the effect of the eruption via health status, test scores, cognitive development, and household earnings and expenditure, as well as labor market outcomes. We use the two-period setup to explore the mechanisms because we do not have annual data on these variables, except for the test scores, where we are able to utilize the event study setup because we can obtain multi-period data from PODES and IFLS.

### 5.4.1 Earnings and spending

In columns 1 and 2 of Table 5, we do not find a statistically significant impact of the volcano eruptions on household earnings and total spending. This might suggest that the volcano eruptions did not substantially change economic opportunities in the area.<sup>24</sup>

When we conduct estimations of the spending components that might be related to disaster coping mechanisms in columns 3 to 6, we find evidence of a spending pattern shift, as households tend to reallocate spending from education towards essential household goods. Column 3 shows that education spending is lower for the treated group after the disaster. Column 4 shows that there is a negative but insignificant impact on health spending, which corroborates the result of the health status mechanism in Table 6. This suggests that health is not a channel of impact for the 2010 Merapi and 2014 Kelud eruptions. Columns 5 and 6 show that spending on durable goods<sup>25</sup> and household supplies and furniture<sup>26</sup>, respectively, is higher for the treated group post-disaster. This suggests that households used education money to recoup essential durable goods, supplies, and furniture that might have been lost or damaged during the disaster. This finding is in line with

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<sup>24</sup>However, we cannot completely rule out the possibility of a drop in earnings and spending in the years immediately following the eruption because our post-treatment data are only from 2014, which is four years after the Merapi eruption and only several months after the Kelud eruption. It is possible that household earnings fell shortly after the impact but have recovered since. We cannot confidently ascertain the story here due to our inability to identify the dynamic year-to-year impact.

<sup>25</sup>This includes vehicles, housing, television sets, cellphones, beds, livestock, etc.

<sup>26</sup>This includes tables, chairs, kitchen tools, bed sheets, towels, etc.



those of Deuchert & Felfe (2015); in the case of Super Typhoon Mike in the Philippines in 1990, they also found a reduction in education spending as one of the channels driving the impact of the disaster on school enrollment.<sup>27</sup> Likewise, Cameron & Worswick (2001) also found that households in Indonesia tend to cut back on educational spending as a response to transitory shocks such as crop loss.

We also posit that it is unlikely that education spending fell because of aid or because schools became free after the disaster. First, there were numerous reports that the amount of disaster relief was insufficient and rather small (Belford 2010; Roberts 2010). There were also reports that parents planned on stopping their children’s enrollment because they could not pay for the schooling costs (Kompas Cyber Media 2011). It is important to remember that while Indonesia has made significant strides in lowering the tuition fees of public schools, schooling costs entail many other hidden and indirect costs, such as the cost of transportation, school attire (uniforms, shoes), and other school supplies (books, stationary).<sup>28</sup> These items were either lost or destroyed during volcanic eruptions (Rahman, Nurhasanah & Nugroho 2016). Finally, school rebuilding was also delayed because the government considered it the second priority after resettlement (PSPK UGM 2010). The study by Rahman, Nurhasanah & Nugroho (2016) documents that children had dropped out of school long before the government even finished erecting the emergency schools.

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<sup>27</sup>Like in our study, Deuchert & Felfe (2015) also observed a fall in education spending four years after the disaster. They even found that the reduction in education spending grows larger in the long run. Another important note is that they found a larger reduction effect in education spending: 9.1% four years after the disaster. Our estimate is much more modest: only 2.5% four years after the disaster.

<sup>28</sup>In our sample, non-tuition education expenditures account for 83% of total household education spending pre-eruption and 74% post-eruption. This number is also likely to be understated. In the IFLS, even the tuition component of education expenditure still consists of many non-tuition items such as parent-teacher committee contributions, student association contributions, registration fees, and other extra fees and contributions (excluding uniforms, transportation, pocket money, and school supplies). These items are largely up to the school’s discretion and unregulated by the government. Unfortunately, due to the way the questionnaire was structured, we are unable to decompose the share of each subitem because they are all lumped together as one question. Nonetheless, we can expect that the true share of the non-tuition expenditure is larger than the number mentioned above.

Table 5: Earnings and spending channels

	Dependent variable:					
	Household earnings (1)	Total spending (2)	Education spending (3)	Health spending (4)	Durable goods spending (5)	Household supplies and furniture spending (6)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.003338 (0.003341)	-0.000364 (0.001483)	-0.024419*** (0.006104)	-0.006023 (0.008514)	0.048061** (0.018815)	0.032096*** (0.012035)
Child's covariates	✓	✓	✓	✓	✓	✓
Parent's covariates	✓	✓	✓	✓	✓	✓
Area's covariates	✓	✓	✓	✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓	✓
Obs.	4,202	4,082	4,193	4,186	4,186	4,186
Adj. R2	0.4437	0.6362	0.1596	0.0969	0.1445	0.0884

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Notes. All dependent variables are in log form.

Source: Authors' calculation

## 5.4.2 Health status

We examine the impact of volcanic eruptions on children's health status, missed activity, and time spent in bed but could not find any detectable impact. Column 1 in Table 6 examines the impact on the binary self-reported health status. In columns 2 and 3, we estimate the impact of the eruption on whether the children ever missed days of activities or stayed in bed due to poor health over the past four weeks. In columns 4 and 5, we estimate the impact of the eruption on the extensive margin of dependent variables in columns 2 and 3 and found an insignificant impact.

Table 6: Health channels

	Dependent variable:				
	Health status (1)	Ever missed activity in past month (2)	Ever in bed in past month (3)	Days missed activity in past month (4)	Days in bed in past month (5)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.000711 (0.000873)	-0.000869 (0.001228)	0.000390 (0.000893)	-0.004584 (0.007554)	-0.001278 (0.003394)
Child's covariates	✓	✓	✓	✓	✓
Parent's covariates	✓	✓	✓	✓	✓
Area's covariates	✓	✓	✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓
Obs.	4,202	4,175	4,176	4,175	4,176
Adj. R2	0.0216	0.0141	0.0380	-0.0167	0.0216

Standard errors in parentheses

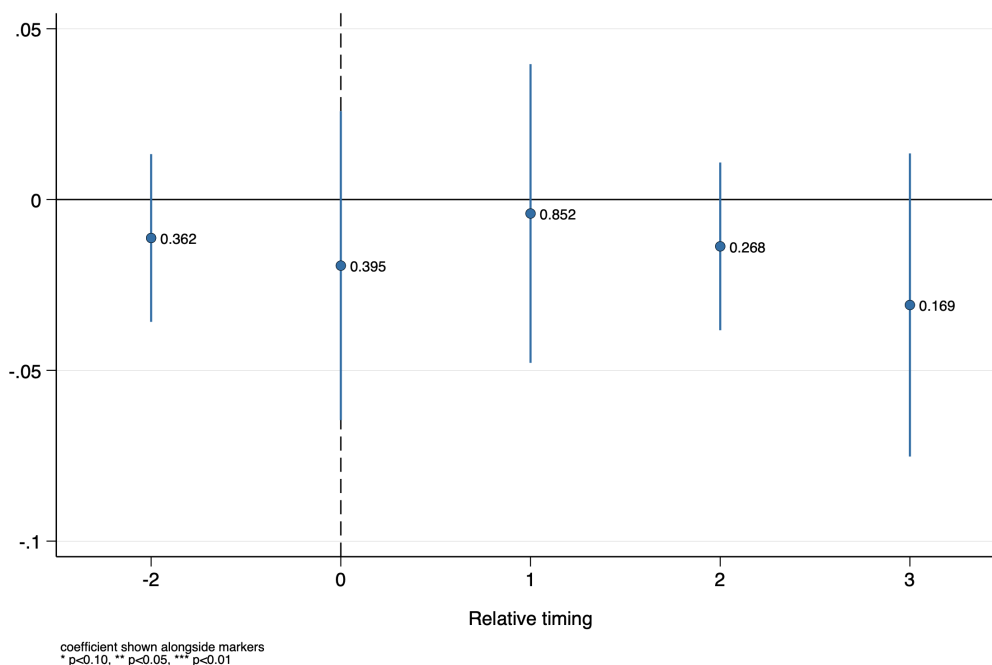
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Source: Authors' calculation

### 5.4.3 Test scores and cognitive development

We do not find any significant effect on children's test scores and cognitive development. The eruption may affect the quality of education; therefore, we construct test scores from the national exam results of all children who continued to go to school. In the last year of each school level, all children are required to participate in national exams for three subjects, which are Mathematics, Bahasa Indonesia, and English. In IFLS5, respondents were asked about their past national exam test scores at the end of each education level, which are primary, lower secondary, and upper secondary. The pre-test score is the children's score in the closest year before the eruption, while the post-test score is from the closest year after the eruption. Since children take the exam at different times, we include the schooling level transition<sup>29</sup> as a fixed effect. The result is conditional on children who remain in school post-eruption; therefore, the sample is reduced to 435 observations and only reflects those who continued to go to school. The results in Table 3 show that the eruption impact on children's test scores is not significant, conditional on those who remain at school.

Figure 3: Test scores



Source: Authors' calculation

We also examine if there is any difference in children's cognitive development. The IFLS provides

<sup>29</sup>This transition can be either from primary to lower secondary or from lower secondary to upper secondary.

a set of questions based on a shorter set of the Raven’s Colored Progressive Matrices tests and five numeracy questions, which are available for the two waves. We construct the share of correct answers for the cognitive test to examine whether the eruption affects children’s cognitive development. Our results in Table 7 show that there is no significant impact of the volcanic eruption on children’s cognitive scores after four years in the Mt. Merapi sample nor after less than a year in the Mt. Kelud sample. This result for all continuing and drop-out children is in line with our previous test score estimation. Our result complements the results in the literature (Sulistyaningrum 2017), as we find that there is no impact on children’s cognitive development when including children who are not continuing school.

Table 7: Cognitive development

	Dep. variable: Cognitive score		
	Mt. Merapi (1)	Mt. Kelud (2)	Stacked (3)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	0.000979 (0.000799)	-0.000311 (0.00118)	0.000504 (0.000675)
Child’s covariates	✓	✓	✓
Parent’s covariates	✓	✓	✓
Area’s covariates	✓	✓	✓
Subdistrict’s latitude and longitude	✓	✓	✓
Time fixed effect	✓	✓	✓
Individual fixed effect	✓	✓	✓
Obs.	2,429	1,773	4,202
Adj. R2	0.160	0.166	0.0130

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: Authors’ calculation

#### 5.4.4 Labor outcomes

The volcano eruption increases the likelihood of children working and dropping out of school. We do not find evidence that volcano eruption affects the probability that children are temporarily absent from school (column 1 in Table 8). However, we find evidence that an eruption increases the likelihood of working in the past 12 months, working and dropping out of school entirely, and not working and not being in school either. If we put the story together, we can interpret this as follows: children are more likely to work when disaster strikes, either while maintaining attendance at school or while skipping classes altogether (column 2, 11.41 percentage points per 100 km). Yet,

when they do have to skip classes, it is unlikely that they skip school only for a short period, as evidenced by the null effect on temporary absenteeism (column 1). It is more likely for them to drop out of school entirely, rather than just skip classes for a short period to help the household earn income (column 3).

As an alternative to working, it is also possible for children to just stay at home, neither working nor being in school after the disaster (column 4). However, the treatment effect for this joint probability is smaller (4.9 percentage points within 100 km) than the treatment effect on working and dropping out (6.79 percentage points within 100 km). In the aftermath of a disaster, there might be factors that keep children at home. For example, children might stay at home to help with increased household tasks after the disaster, such as caring for the elderly and the sick, repairing the house, or taking over household tasks that were previously handled by a household member who unfortunately passed away in the disaster. Children might also be constrained by gender roles or household obligations, which further keeps them from returning to school (Hamidazada, Cruz & Yokomatsu 2019).

Our finding is in line with those of Caruso (2017) in the case of various natural disasters in Latin America, Santos (2007) in the case of the 2001 earthquake in El Salvador, and Bustelo (2011) in the case of Tropical Storm Stan in Guatemala in 2005; these authors found an increase in child labor as a form of family insurance in the aftermath of disaster. Yet unlike Baez & Santos (2007), who only found an impact on increased child labor force participation and no impact on enrollment, we found that the natural disaster in our case actually affects the probability of both.

Table 8: Absenteeism, dropouts, and labor outcomes

	Dependent variable:			
	Temporarily absent from school	Working in the past 12 months	Working and dropping out	Not working and dropping out
	(1)	(2)	(3)	(4)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.000183 (0.000289)	0.001141** (0.000543)	0.000679** (0.000356)	0.000493* (0.000299)
Child's covariates	✓	✓	✓	✓
Parent's covariates	✓	✓	✓	✓
Area's covariates	✓	✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓
Obs.	4,202	4,202	4,202	4,202
Adj. R2	0.0099	0.0788	0.0340	0.0739

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Source: Authors' calculation

## 5.5 Heterogeneity analysis

We are interested in examining differential impacts in terms of gender, urban/rural residential status, birth order, schooling level during the eruption, and socioeconomic status. These are all aspects that the literature has shown to be important determinants of school enrollment (Takahashi 2011). In this instance, we analyze heterogeneity by interacting the group dummy variable with the triple difference.<sup>30</sup> Table 9 presents the results of group heterogeneity estimation.

The first column shows heterogeneity across gender. We find that the negative treatment effect is slightly larger for females. This finding is in line with the existing literature on the impact of natural disasters on girls' education, which highlights the vulnerabilities and challenges that girls face in accessing education (Matsumoto-Royo, Ramírez-Montoya & Glasserman-Morales 2022; Neumayer & Plümper 2007). In settings where conservative gender roles and unequal power relations persist, girls' education is undermined, which then contributes to young girls' vulnerability during disasters (Hamidazada, Cruz & Yokomatsu 2019).

The second column shows treatment effects across the living area. We do not find evidence that children in urban or rural areas have heterogeneous treatment impacts compared to our full sample. One explanation for this is that we might have already absorbed the urban-rural dynamics by controlling heterogeneity in the distance from the peak in the triple difference. The third column

<sup>30</sup>Hence, there is no excluded group since one of the variables in the triple difference is continuous (distance).

shows the heterogeneity of treatment considering birth order. We find a statistically significant impact only for the oldest children in the household<sup>31</sup>. It has been widely documented in the literature that the dropout risk is higher for older children. Adverse events such as natural disasters can easily push those who are already on the brink of dropping out to leave school altogether (Baez, de la Fuente & Santos 2010).

The treatment effect is larger and only statistically significant for primary-school-aged children during the eruption, although secondary-school-aged children also have a negative treatment effect. The results indicate that disruption at an early age has a more significant negative impact on school continuation compared to disruption at a later age. This result is consistent with Shidiqi, Di Paolo & Choi (2023) and Bustelo, Arends-Kuenning & Lucchetti (2012), who also identify more severe disruption effects for primary school students and that the severity of the impact wanes with age for the 2006 Jogjakarta earthquake and 1999 Colombian earthquake, respectively. However, our sample construction filters in children who are enrolled during the eruption; it could be the case that children who are enrolled in secondary school during the eruption are older children who are more likely to stay enrolled in school to begin with, given that they are still in school even though the risk of dropout is already higher for them. This might explain why there is no statistically significant impact on secondary school students.

Finally, the fifth column shows that the treatment effect is larger and only statistically significant for poor households<sup>32</sup>. This is hardly surprising, as poor households have a more limited ability to cope with the disaster; hence, they are predisposed to bear the brunt of the shock.

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<sup>31</sup>Note that the treatment coefficient is actually larger for the birth order  $\geq 3$ . However, since the number of children with such a birth order is smaller, the standard error is larger as well, hence, the statistically insignificant impact for the group.

<sup>32</sup>We define a poor household as a household that receives help from a social assistance program.

Table 9: Heterogeneity across groups

	Dependent variable: School enrollment				
	Gender	Urban	Birth order	School level	Socioeconomic status
	(1)	(2)	(3)	(4)	(5)
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Male } (=0)$	-0.001258** (0.000741)				
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Male } (=1)$	-0.001131* (0.000612)				
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Urban } (=0)$		-0.000847 (0.001096)			
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Urban } (=1)$		-0.001043 (0.000647)			
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Birth order } (=1)$			-0.001225* (0.000689)		
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Birth order } (=2)$			-0.000844 (0.000745)		
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Birth order } (\geq 3)$			-0.002213 (0.001778)		
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Primary } (=1)$				-0.001986*** (0.000666)	
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Primary } (=0)$				-0.000298 (0.000811)	
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Poor } (=1)$					-0.002575** (0.000997)
$Treat_{ist}(=1) \cdot Post_{t=1} \cdot Distance_{ist} \cdot \text{Poor } (=0)$					-0.000323 (0.000490)
Child's covariates	✓	✓	✓	✓	✓
Parent's covariates	✓	✓	✓	✓	✓
Area's covariates	✓	✓	✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓
Obs.	3,987	3,987	3,987	3,987	3,987
Adj. R2	0.0693	0.0709	0.0659	0.0728	0.0743

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Notes. All heterogeneity variables that could possibly be time-invariant are variables acquired from the baseline. The time-variant heterogeneity variables are the residential location (urban or rural areas) and household socioeconomic status.

Source: Authors' calculation

## 5.6 Mediating factors to improve resilience

We conduct a mediation analysis to dissect what viable policy interventions can buffer the adverse shock. Following Imai et al. (2011), we do this by adding a mediation variable<sup>33</sup> in the estimation and observing the average causal mediation effect (ACME). The ACME is the difference between treatment estimates with and without the mechanism variable. We are interested in what we call demand- and supply-side infrastructure, both of which can be influenced by policymakers. Demand-side factors affect the household's decision to send their children to school. Meanwhile, supply-side infrastructure relates more to the capability of the educational system to absorb adverse shocks and ensure that children stay in school. Operationally, we conduct our mediation analysis by adding

<sup>33</sup>The mediation variable is a time-variant variable, just like most of our covariates. We obtain the variables from the two waves of data.



mediating variables in the estimation and observe whether it mediates or worsens the treatment effect (Imai, Keele & Tingley 2010; MacKinnon, Fairchild & Fritz 2007; MacKinnon, Krull & Lockwood 2000).

### 5.6.1 Demand-side mediation

Out of the four demand mediation variables, only good phone signals mediate the negative impact (Table 10, column 3). On its own, a strong phone signal has a positive direct effect on school enrollment while also reducing the treatment effect to 6.8 percentage points. We posit that a good telecommunication network could help students to learn from home and also help children to continue studying during school closures due to an eruption.

In column 1, we find that better road infrastructure slightly worsens the treatment effect. Meanwhile, good roads on their own reduce enrollment, although the coefficient is statistically insignificant. According to MacKinnon, Krull & Lockwood (2000), there are two frameworks for understanding why the inclusion of a covariate enlarges the treatment effect instead of shrinking it. The first is “inconsistent mediation” or “suppression.” In this framework, the eruption affects enrollment via road quality by destroying roads. A poorer road quality then lowers enrollment. However, for this argument to be true, we need a positive sign in the coefficient of the asphalt road variable, which we do not have in this case. Thus, the more likely scenario is the second framework, which MacKinnon, Krull & Lockwood (*ibid.*) call “negative confounding.” In this framework, the eruption affects enrollment via road quality because good roads can worsen enrollment by allowing children to transition into the labor force more conveniently when an adverse shock occurs. Given that the coefficient sign of the asphalt road variable is negative, the latter framework seems a more appropriate interpretation for our case.

Table 10: Demand-side mediating factors

	Dep. variable: School enrollment			
	(1)	(2)	(3)	(4)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.00121** (0.000561)	-0.00191*** (0.000611)	-0.00102* (0.000560)	-0.00192*** (0.000591)
Asphalt road <sub>st</sub>	-0.0103 (0.0281)			
Access to loans <sub>st</sub>		-0.0139 (0.0194)		
Strong phone signal <sub>st</sub>			0.184*** (0.0650)	
Access to factory <sub>st</sub>				-0.0101 (0.0132)
Obs.	3,558	2,835	3,978	2,835
Adj. R2	0.0912	0.0357	0.0990	0.0358

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Notes. The asphalt road variable is the share of villages in a subdistrict with asphalt roads or other paved roads, dirt roads, and others. The access to loan variable indicates whether the household has access to a loan in the community. Disaster assistance indicates whether the household received any type of assistance during the eruption. Strong phone signal indicates the share of villages in a subdistrict with a strong or very strong phone signal instead of a weak phone signal or none. Access to a factory indicates whether there is a factory in the community where the household lives.

Source: Authors' calculation

Much of the literature has emphasized the importance of access to finance as an instrument of consumption smoothing during adverse events (Bandara, Dehejia & Lavie-Rouse 2015; Beegle, Dehejia & Gatti 2006; Jacoby & Skoufias 1997). Yet in our case, the inclusion of having access to loans in the community worsens the impact of a volcano eruption on children's schooling from 8.1 to 12.8 percentage points (column 2). Once again, the appropriate framework to interpret these statistical results is "negative confounding" since the coefficient sign on access to loans is negative (MacKinnon, Krull & Lockwood 2000). We argue that an eruption affects enrollment via access to loans by driving households into deeper problems of indebtedness, which then worsens the negative treatment effect on enrollment.

Another factor that might be related to coping mechanisms during disasters is access to economic opportunities in the area. Thus, we examine whether access to a factory in the community mediates the treatment effect. We find that the negative treatment effect is larger after the inclusion of this variable (column 4). The direct effect of this variable is negative for school enrollment, although

it is statistically insignificant. A volcanic eruption affects enrollment by increasing the likelihood of child labor, and the close presence of a factory in the community further raises the opportunity costs of sending children to school, thus worsening the treatment impact.

### 5.6.2 Supply-side mediation

Table 11 shows that a larger number of schools, an improved children-school ratio, and an improved pupil-teacher ratio could improve education resilience against the impact of an eruption. The total number of schools (column 1) in the community mediates the treatment effect from 8.1 to 7.3 percentage points. There are many ways better school availability can help absorb the adverse impact of this shock. For one, more school buildings mean more facilities that can be used as temporary schools for children whose schools are damaged or under repair after the disaster. The direct effect of more schools on its own on enrollment is positive but statistically insignificant.

Table 11: Supply-side mediating factors

	Dep. variable: School enrollment		
	(1)	(2)	(3)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.001095* (0.000575)	-0.001212** (0.000558)	-0.001494** (0.000581)
Number of schools <sub>st</sub>	0.000716 (0.000574)		
Children-school ratio <sub>st</sub>		0.0108 (0.00929)	
Pupil-teacher ratio <sub>st</sub>			0.0114 (0.007874)
Obs.	3,987	3,552	3,852
Adj. R2	0.0688	0.0937	0.0741

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Notes. The children-school ratio and pupil-teacher ratio are both in log form. We use SUSENAS to calculate the population of children in each district and PODES to aggregate the number of schools in each district. Meanwhile, we draw on the IFLS community survey to construct the pupil-teacher ratio.

Source: Authors' calculation

The second and third columns show that higher children-school and pupil-teacher ratios worsen the treatment effect. The pupil-teacher ratio has a greater suppression or inconsistent mediation effect, as does as the children-school ratio variable, as it worsens the treatment effect magnitude from 8.1 to 10 percentage points, while the treatment effect with the children-school ratio is similar.

The children-school ratio tells us how many school-age children there are for every school in the district. It is essentially an indication of whether the number of schools in the area is sufficient to allow all of the school-age children (enrolled or not) to be students. Meanwhile, the pupil-teacher ratio more closely represents the education system’s actual workload. It is a measure of how many students there are per teacher. A higher number means a greater workload for the teacher. In the event of a disaster, resource and personnel numbers will be even more strained. Under such pressure, it becomes increasingly arduous for them to do anything to help children stay in school. It is then intuitive that students whose teachers have a higher workload will have a higher probability of dropping out after the disaster. This is consistent with a huge body of literature that has emphasized the importance of teachers’ availability and presence in influencing student’s achievements and attendance (ACDP 2014; McKenzie et al. 2014; Rogers & Vegas 2009).

## 6 Discussions

Our findings add to the literature, supporting the idea that transitory disruption in children tends to be long-lasting and that they are unlikely to recover quickly. Children whose school attendance has been disrupted are unlikely to continue studying and are more likely to work. This then shapes a different future trajectory compared to those whose school attendance was never disrupted (Baez, de la Fuente & Santos 2010; de Janvry et al. 2006; De Vreyer, Guilbert & Mesple-Somps 2015). Our study uses children initially enrolled in primary and lower secondary school, with school enrollment as the main outcome, and an individual level identification strategy; hence, we differ from several previous studies (De Vreyer, Guilbert & Mesple-Somps 2015; Jensen 2000; Rush 2014, 2018; Yamauchi, Yohannes & Quisumbing 2009).

We identify six comparable studies (Table 12), and our treatment effect size in the stacked sample is closest to that of the 1999 Colombian earthquake (Bustelo, Arends-Kuenning & Lucchetti 2012). Meanwhile, our treatment effect size in the Merapi estimation sample only is similar to that of Tropical Storm Stan in Guatemala in 2005 (Bustelo 2011). The impact of a volcano eruption on enrollment in our study is larger than the effects of Super Typhoon Mike on Cebu Island in the Philippines in 1990 (Deuchert & Felfe 2015), several waves of floods in Vietnam in the 1990s and 2000s (Nguyen & Minh Pham 2018), and Hurricane Mitch in Nicaragua in 1998 (Ureta 2005).

Meanwhile, from these six studies, one does not find a statistically significant impact on school enrollment (Baez & Santos 2007).

Table 12: Comparison of effect size

Study	Natural disaster	Effect size on school enrollment
Bimardhika and Moorena (2024)	Volcano eruption	8.1 pp (stacked) 13.3 pp (Merapi)
Deuchert & Felfe (2015)	Typhoon	3.7–7.8 pp
Nguyen & Minh Pham (2018)	Flood	4.9 pp
Bustelo (2011)	Tropical storm	20.8 pp among junior-secondary-age children (13–15 years old) No significant impact among primary-school-age children
Bustelo, Arends-Kuenning & Lucchetti (2012)	Earthquake	7.7–15.5 pp
Ureta (2005)	Hurricane	0.022 pp (only among urban children)
Baez & Santos (2007)	Hurricane	No statistically significant impact

Source: (Baez & Santos 2007; Bustelo 2011; Bustelo, Arends-Kuenning & Lucchetti 2012; Deuchert & Felfe 2015; Nguyen & Minh Pham 2018; Ureta 2005), and authors' calculation

As we have demonstrated in the mediation analysis, there are three potential avenues of intervention to improve education resilience against disaster. The first direct intervention in the education arena is to increase school availability. This is especially important for secondary-school-age children, as the number of secondary public schools is lower than that of their private counterparts (Suharti 2013). In addition, our event study result shows that the negative treatment effect grows larger over time. This means that the older the eruption-exposed children become, the less likely they are to attend school; this is consistent with the trend that the enrollment rate tends to drop sharply from primary to secondary school.

Another intervention in the education infrastructure is improving teachers' workload balance. The teacher workload imbalance in Indonesia is primarily driven by the uneven distribution of teachers (World Bank 2008). Improving equity in this regard, as well as in terms of other types of resource allocation, such as funding, may help in strengthening the resilience of the education system against adverse shocks. Reducing pupil-teacher ratios can also help to enhance the quality of education and support individualized learning, especially in the context of natural disasters, where interventions might need to be more tailored to children's unique needs and circumstances (Raccanello, Burro & Hall 2017; Silverman & La Greca 2002).

Another intervention is to improve the telecommunication network in the region. When disaster strikes and the government implements school closures, remote teaching during disasters, such as that implemented during the COVID-19 pandemic, might be a viable intervention to help minimize the harmful impacts of an eruption. Improving internet and phone signals can enhance the feasibility of this intervention.

Finally, we also would like to reemphasize the possibility that the treatment effect varies across time. The event study results have depicted this. However, it is important to also be mindful of this when interpreting the treatment effect under the two-period setup. Note that since the endline data are from 2014, the two-period setup actually estimates the four-year impacts of the Merapi eruption and only several months of impacts for the Kelud eruption. Data collection for IFLS5 occurred in late 2014, while Kelud erupted early in the year. This could partially explain why the Merapi treatment effect is larger than the stacked estimation. Thus, it is possible that the Kelud eruption would exhibit a statistically significant impact if a longer post-treatment period was considered.

## 7 Conclusions

This paper estimates the impact of volcano eruption on children’s schooling in Java Island, Indonesia. Combining a rich panel survey, nationally representative village-level census plus district-level industry survey, and geodistance data, we investigate heterogeneous changes in children’s schooling in response to the shock of volcano eruption and the channel in which the disruption affects school enrolment. We exploit the exogenous timing of the volcano eruption by using the triple difference of treatment status, and year of eruption with continuous treatment using distance to the volcano’s peak to identify the treatment effect.

To ensure comparable treatment and control group, we limit the sample to those living in a 120-kilometer radius of the treatment and control volcanoes, examine the robustness to parallel trend testing, covariates balance, covariates inclusion, and alternative specifications. Our result indicates that volcano eruption causes a decrease in the likelihood of children’s school enrolment. This effect appears to be larger in the medium run of six months to four years. The reallocation of education spending to cope with the adverse shock of the disaster seems to be the driving factor behind the impact. We found that the impact is disproportionate towards girls, the oldest child, primary schoolers, and children from poor households. We also found that the disruption can cause children to transition out of school into the labor force.

We suggest several interventions to mediate the negative impact of the disaster, namely improving school availability, and pupil-teacher ratio, and establishing a good telecommunication network in the local area. While the specific impact of natural disasters on children’s schooling may vary

depending on the context and the severity of the natural disaster, the mediating factors that we tested are important considerations in disaster management and recovery efforts.

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# Appendix

## Appendix A Robustness checks

### A.1 Kelud treatment effect with 500 km catchment area

Table A1: Estimation of Kelud treatment effects when including samples in the Merapi catchment area as treatment units

	School enrollment
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.0005086 (0.0003296)
Child's covariates	✓
Parent's covariates	✓
Area's covariates	✓
Subdistrict's latitude and longitude	✓
Time fixed effect	✓
Individual fixed effect	✓
Obs.	2,638
Adj. R2	0.0494

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### A.2 Various radius

Table A2: Treatment effects under various radii to volcano

	Dep. variable: School enrollment							
	Merapi				Kelud			
	≤120 km	≤100 km	≤80 km	≤60 km	≤120 km	≤100 km	≤80 km	≤60 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.0020683* (0.000803)	-0.0015816 (0.0011724)	-0.0024718 (0.0017463)	-0.0063184** (0.0030678)	0.0000776 (0.0004503)	0.0000691 (0.0004474)	-0.0007677 (0.0009285)	-0.0024387 (0.0022311)
Child's covariates	✓	✓	✓	✓	✓	✓	✓	✓
Parent's covariates	✓	✓	✓	✓	✓	✓	✓	✓
Area's covariates	✓	✓	✓	✓	✓	✓	✓	✓
Subdistrict's lat. and long.	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	2,325	1,952	1,502	1,124	1,662	1,393	992	598
Adj. R2	0.0531	0.0397	0.0491	0.0293	0.0839	0.0754	0.1988	0.1566

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Note that while Merapi's treatment effect is statistically insignificant at 100 and 80 km due to larger standard errors, the sign of the coefficient is consistently negative throughout.

### A.3 Covariate inclusion

Table A3: Sensitivity test of covariates and individual fixed effect inclusion

	Dep. variable: School enrollment			
	(1)	(2)	(3)	(4)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.000997* (0.000519)	-0.00124** (0.000514)	-0.00119** (0.000529)	-0.00118** (0.000537)
Rainfall				-0.00000795 (0.00245)
Child's covariates		✓	✓	✓
Parent's covariates		✓	✓	✓
Area's covariates		✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓
Individual fixed effect			✓	✓
Obs.	4317	3987	3987	3987
Adj. R2	0.0367	0.0724	0.0682	0.0688

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Notes. Precipitation or rainfall data are from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data.

### A.4 Alternative covariates

Table A4: Sensitivity test of alternative covariates

	Dep. variable: School enrollment			
	(1)	(2)	(3)	(4)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.0011985** (0.0005249)	-0.0011796** (0.0005465)	-0.0011975** (0.0005363)	-0.0011893** (0.0005245)
Household size	✓		✓	
Number of dependents and children		✓		✓
Use electricity	✓	✓		
House made of masonry			✓	✓
Child's covariates	✓	✓	✓	✓
Parent's covariates	✓	✓	✓	✓
Area's covariates	✓	✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓
Individual fixed effect	✓	✓	✓	✓
Obs.	3,987	3,987	3,987	3,987
Adj. R2	0.0682	0.0680	0.0675	0.0673

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Appendix B Subdistrict balance

The coefficient for both the treatment status and the interaction term between the treatment and distance to the volcano is statistically insignificant for both the subdistrict area size (measured in square kilometers) and children population density (obtained by dividing the number of children in our sample by the area size). This implies that the distributions of the subdistrict size for the treatment and control are not widely different; hence, the errors in sample selection are distributed evenly between the treatment and control.

Table A5: Subdistrict size balance

	Subdistrict area size (km sq)	Children population density
Treatment	-8.591 (15.41)	0.171 (0.361)
Distance	0.308* (0.160)	0.00183 (0.00342)
Treatment#Distance	-0.0339 (0.208)	-0.00624 (0.00487)
Obs.	402	402

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



## Appendix C Covariate balance across time

In the Merapi sample, only the age of the children is imbalanced over time. In the Kelud sample, only 3 out of 23 covariates are imbalanced. They are the urban-rural status, the household size, and the father's occupation as a casual worker. Please refer to Table [A6](#) for the full results.

Table A6: Covariate balance across time

Covariate as dependent variable	Sample	
	Mt. Merapi	Mt. Kelud
Child is male	-0.000126 (0.000140)	-0.000143 (0.000158)
Age of children	0.00426** (0.00182)	0.00356 (0.00251)
Living in urban area	0.00448 (0.00319)	0.00836* (0.00475)
Household size	-0.00209 (0.00728)	-0.0161* (0.00862)
Male household head	0.00186 (0.00133)	0.000491 (0.00130)
Father's year of schooling	0.0127 (0.00942)	0.00265 (0.0105)
Father's age	0.0240 (0.0494)	0.00313 (0.0470)
Father is Muslim	-1.30e-05 (0.000321)	0.000298 (0.000537)
Father is self-employed	-0.000609 (0.00181)	-0.00121 (0.00276)
Father is government worker	0.000688 (0.000508)	0.000585 (0.000506)
Father is private worker	0.000103 (0.00168)	-0.00323 (0.00318)
Father is casual worker	0.00172 (0.00144)	0.00246** (0.00121)
Father is not working / unpaid worker	-0.00154 (0.00107)	0.000451 (0.00149)
Mother's year of schooling	0.00440 (0.00880)	-3.09e-05 (0.00809)
Mother's age	0.00566 (0.0368)	-0.0116 (0.0319)
Mother is Muslim	0.000180 (0.000295)	0.000132 (0.000267)
Mother is self-employed	0.00131 (0.00112)	0.000611 (0.00143)
Mother is government worker	0.000410 (0.000324)	0.000553 (0.000375)
Mother is private worker	-0.000889 (0.000930)	-0.00201 (0.00147)
Mother is casual worker	-0.000381 (0.00105)	0.000432 (0.00141)
Mother is not working / unpaid worker	-0.000799 (0.00145)	-0.000267 (0.00235)
Industry employment growth	-0.00291 (0.00230)	-0.00119 (0.00216)
Have access to electricity	0.000209 (0.000634)	-0.000252 (0.000272)
Obs.	2,648	1,888

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Appendix D Baseline matching

We use the baseline characteristics in the 2007 IFLS and perform matching using the nearest neighbor with the replacement method and the entropy balancing method. The benefit of this approach is the construction of a comparison group based on the observed characteristics that influence the probability of treatment assignment. Then, using the individuals within the common support, we estimate the treatment effect of the volcano eruption on children’s schooling. Households living in areas vulnerable to volcanic activity may have unique characteristics related to their livelihood, education, or demographics, a concern that the combined matching and triple difference method helps alleviate. Thereby, we include the socio-economic and demographic characteristics of children, their parents, the household, and the area to ensure the effectiveness of the probability of treatment assignment. In the triple difference estimation, we also include individual fixed effects to mitigate any time-invariant unobserved characteristics that may confound the treatment effect.

### D.1 Propensity score matching

The PSM method used is single nearest-neighbor matching with replacement. The matching result shows that there are significant masses of both groups across the common support where the distributions of the propensity scores for the treatment and comparison groups overlap. The off-support region is also small (Figure A2). The variance ratio of the variables is close to one (Figure A1).

Figure A1: Propensity score distribution of treatment assignment

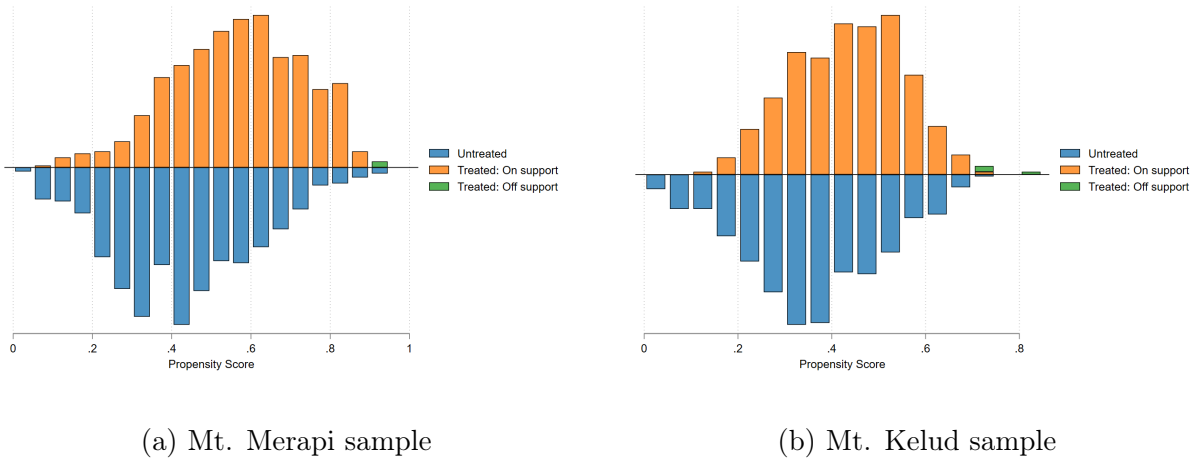
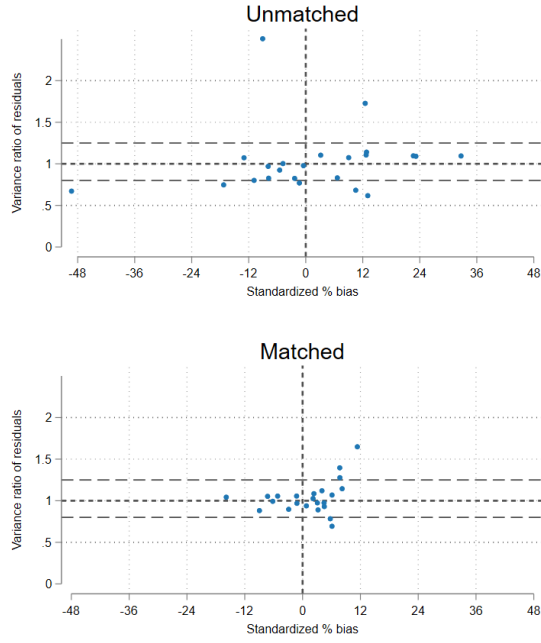
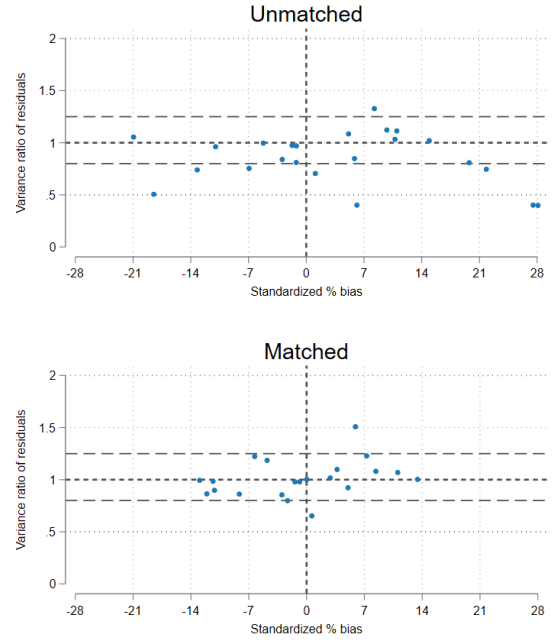


Figure A2: Covariate balance post-PSM



(a) Mt. Merapi sample



(b) Mt. Kelud sample

We provide the full matching results, including the covariate balance for baseline pre-matching, in the table below.

Table A7: Full matching results: Merapi

Variable	Unmatched	Mean		Bias		t-test		V <sub>e</sub> (T)/
	Matched	Treated	Control	%bias	%reduct	t	p> t	V <sub>e</sub> (C)
Child is male	U	0.50472	0.52886	-4.8		-0.86	0.388	1.01
	M	0.50553	0.48341	4.4	8.4	0.79	0.432	0.98
Age of children	U	8.8632	8.6069	12.7		2.26	0.024	1.11
	M	8.8657	8.7852	4	68.6	0.71	0.475	1.12
Living in urban area	U	0.53774	0.60218	-13		-2.33	0.02	1.08
	M	0.5387	0.50869	6.1	53.4	1.07	0.285	1.07
Household size	U	9.1447	9.209	-2.4		-0.42	0.671	0.83
	M	9.1517	9.0695	3	-27.6	0.56	0.577	0.98
Male household head	U	0.89623	0.8752	6.6		1.18	0.238	0.83
	M	0.89573	0.88152	4.5	32.4	0.8	0.422	0.93
Father's year of schooling	U	8.6557	7.6677	23.1		4.13	0	1.09
	M	8.6445	8.8673	-5.2	77.5	-0.92	0.359	1.06
Father's age	U	38.967	39.142	-1.4		-0.25	0.806	0.77*
	M	38.983	38.886	0.8	44.9	0.14	0.887	0.94
Father is Muslim	U	0.94654	0.92044	10.5		1.87	0.061	0.68*
	M	0.94629	0.93839	3.2	69.7	0.6	0.547	0.89
Father is self-employed	U	0.41038	0.30265	22.6		4.04	0	1.1
	M	0.40916	0.44392	-7.3	67.7	-1.25	0.212	1.05
Father is government worker	U	0.08491	0.07644	3.1		0.55	0.579	1.11
	M	0.08531	0.07899	2.3	25.3	0.41	0.683	1.09
Father is private worker	U	0.25629	0.28081	-5.5		-0.99	0.323	0.93
	M	0.25592	0.24645	2.1	61.3	0.39	0.698	1.03
Father is casual worker	U	0.09434	0.11856	-7.9		-1.4	0.161	0.83
	M	0.09479	0.07109	7.7	2.2	1.53	0.127	1.40*
Father is not working / unpaid worker	U	0.15409	0.22153	-17.3		-3.09	0.002	0.75*
	M	0.15482	0.15956	-1.2	93	-0.23	0.817	0.97
Mother's year of schooling	U	8.6069	7.2715	32.6		5.83	0	1.1
	M	8.575	8.6272	-1.3	96.1	-0.23	0.821	1.06
Mother's age	U	36.921	36.103	9		1.61	0.108	1.08
	M	36.913	37.731	-9	0	-1.5	0.133	0.88
Mother is Muslim	U	0.94969	0.91732	13		2.32	0.02	0.62*
	M	0.94945	0.93523	5.7	56.1	1.08	0.278	0.79*
Mother is self-employed	U	0.23428	0.18253	12.8		2.28	0.023	1.14
	M	0.23381	0.20063	8.2	35.9	1.43	0.153	1.15
Mother is government worker	U	0.06289	0.03588	12.5		2.23	0.026	1.73*
	M	0.06319	0.06951	-2.9	76.6	-0.45	0.652	0.9
Mother is private worker	U	0.12264	0.16069	-10.9		-1.95	0.051	0.8
	M	0.12322	0.09637	7.7	29.4	1.53	0.127	1.28*
Mother is casual worker	U	0.05189	0.05304	-0.5		-0.09	0.926	0.98
	M	0.05213	0.02686	11.3	-2087.8	2.31	0.021	1.65*
Mother is not working / unpaid worker	U	0.5283	0.56786	-7.9		-1.42	0.156	0.97
	M	0.52765	0.60664	-15.9	-99.7	-2.84	0.005	1.04
Industry employment growth	U	0.00492	0.04156	-49.3		-8.81	0	0.67*
	M	0.00515	0.00977	-6.2	87.4	-1.3	0.195	1
Have access to electricity	U	0.98428	0.99376	-9.1		-1.63	0.104	2.51**
	M	0.98578	0.97946	6.1	33.4	0.86	0.39	0.70*

Table A8: Full matching results: Kelud

Variable	Unmatched	Mean		Bias		t-test		$V_e(T)/V_e(C)$
	Matched	Treated	Control	%bias	%reduct	t	$p> t $	
Child is male	U	0.48045	0.53546	-11		-1.63	0.104	0.96
	M	0.48451	0.5493	-13	-17.8	-1.73	0.084	1
Age of children	U	8.4693	8.289	9.8		1.45	0.146	1.12
	M	8.4507	8.2028	13.4	-37.5	1.78	0.075	1
Living in urban area	U	0.49721	0.60106	-21		-3.11	0.002	1.06
	M	0.49577	0.48169	2.8	86.4	0.37	0.708	1.02
Household size	U	8.9581	9.1436	-7		-1.01	0.311	0.75*
	M	8.9718	9.0338	-2.3	66.6	-0.31	0.754	0.8
Male household head	U	0.89944	0.88121	5.8		0.86	0.392	0.85
	M	0.89859	0.91831	-6.3	-8.1	-0.91	0.363	1.22
Father's year of schooling	U	8.4693	7.8493	14.9		2.2	0.028	1.02
	M	8.4056	8.6056	-4.8	67.7	-0.67	0.504	1.19
Father's age	U	38.997	38.865	1.1		0.16	0.876	0.71*
	M	38.955	40.33	-11.2	-941.7	-1.54	0.124	0.9
Father is Muslim	U	0.97765	0.91667	27.5		3.84	0	0.40**
	M	0.97746	0.97746	0	100	0	1	1
Father is self-employed	U	0.34358	0.29255	11		1.63	0.103	1.12
	M	0.34366	0.4	-12.1	-10.4	-1.55	0.121	0.87
Father is government worker	U	0.03911	0.08333	-18.5		-2.64	0.008	0.51*
	M	0.03944	0.02535	5.9	68.2	1.06	0.29	1.51*
Father is private worker	U	0.32961	0.28014	10.7		1.6	0.11	1.04
	M	0.32676	0.27606	11	-2.5	1.47	0.141	1.07
Father is casual worker	U	0.12011	0.12411	-1.2		-0.18	0.857	0.97
	M	0.12113	0.12394	-0.9	29.6	-0.11	0.909	0.98
Father is not working / unpaid worker	U	0.1676	0.21986	-13.2		-1.94	0.053	0.74*
	M	0.16901	0.17465	-1.4	89.2	-0.2	0.843	0.98
Mother's year of schooling	U	8.2709	7.4433	21.8		3.17	0.002	0.75*
	M	8.2056	8.5155	-8.2	62.6	-1.14	0.255	0.86
Mother's age	U	35.835	35.94	-1.2		-0.18	0.857	0.81
	M	35.8	35.377	5	-304.3	0.7	0.484	0.92
Mother is Muslim	U	0.97765	0.91489	28.1		3.92	0	0.40**
	M	0.97746	0.97746	0	100	0	1	1
Mother is self-employed	U	0.17598	0.18262	-1.7		-0.26	0.798	0.98
	M	0.17746	0.16338	3.7	-111.9	0.5	0.618	1.1
Mother is government worker	U	0.03352	0.03901	-2.9		-0.43	0.667	0.84
	M	0.0338	0.03944	-3	-2.7	-0.4	0.69	0.86
Mother is private worker	U	0.17318	0.15426	5.1		0.76	0.447	1.09
	M	0.16901	0.13803	8.4	-63.7	1.14	0.253	1.08
Mother is casual worker	U	0.06704	0.04787	8.2		1.24	0.215	1.33*
	M	0.06761	0.0507	7.3	11.8	0.95	0.341	1.23
Mother is not working / unpaid worker	U	0.55028	0.57624	-5.2		-0.77	0.439	1
	M	0.55211	0.60845	-11.3	-117	-1.52	0.129	0.99
Industry employment growth	U	0.05459	0.03998	19.7		2.87	0.004	0.81
	M	0.05438	0.05392	0.6	96.9	0.08	0.937	0.65*
Have access to electricity	U	0.99721	0.99291	6.1		0.87	0.387	0.40**
	M	0.99718	1	-4	34.5	-1	0.318	.

## D.2 Entropy balancing

As a comparison, we also utilize the entropy balancing matching method. While PSM matches the propensity scores, entropy balancing performs matching based on the covariate’s moments, which are its mean, variance, and skewness (Hainmueller 2012). The entropy balancing results show that the three moments of the covariates are more balanced after matching (Table A9 to Table A12).

Table A9: Before weighting (Merapi sample)

	Treatment			Control		
	Mean (1)	Variance (2)	Skewness (3)	Mean (4)	Variance (5)	Skewness (6)
Gender	0.5047	0.2504	-0.01887	0.5289	0.2496	-0.1156
Age	8.863	4.354	0.2913	8.607	3.83	0.3772
Urban	0.5377	0.249	-0.1514	0.6022	0.2399	-0.4175
Household size	9.145	6.637	1.067	9.209	8.031	1.121
Gender of household head	0.8962	0.09315	-2.598	0.8752	0.1094	-2.27
Father’s length of schooling	8.656	18.89	0.08098	7.668	17.57	0.1083
Father’s age	38.97	140.1	-0.4676	39.14	182.4	0.1462
Father is Muslim	0.9465	0.05068	-3.97	0.9204	0.07335	-3.107
Father is self-employed	0.4104	0.2423	0.3644	0.3027	0.2114	0.8591
Father is government worker	0.08491	0.07782	2.978	0.07644	0.07071	3.188
Father is private worker	0.2563	0.1909	1.116	0.2808	0.2023	0.9755
Father is casual worker	0.1541	0.1306	1.916	0.2215	0.1727	1.341
Mother’s length of schooling	8.607	17.34	-0.02639	7.271	16.14	0.2485
Mother’s age	36.92	86.12	1.19	36.1	79.39	0.7584
Mother is Muslim	0.9497	0.04786	-4.114	0.9173	0.07597	-3.031
Mother is self-employed	0.2343	0.1797	1.255	0.1825	0.1494	1.644
Mother is government worker	0.1226	0.1078	2.301	0.1607	0.1351	1.848
Mother is private worker	0.05189	0.04927	4.041	0.05304	0.05031	3.989
Mother is casual worker	0.5283	0.2496	-0.1134	0.5679	0.2458	-0.274
Industry employment growth	0.004915	0.004172	0.9483	0.04156	0.00686	0.8568
Use electricity	0.9843	0.0155	-7.786	0.9938	0.006211	-12.54

Table A10: After weighting (Merapi sample)

	Treatment			Control		
	Mean (1)	Variance (2)	Skewness (3)	Mean (4)	Variance (5)	Skewness (6)
Gender	0.5047	0.2504	-0.01887	0.5047	0.2504	-0.01887
Age	8.863	4.354	0.2913	8.863	4.354	0.2913
Urban	0.5377	0.249	-0.1514	0.5377	0.249	-0.1514
Household size	9.145	6.637	1.067	9.145	6.637	1.067
Gender of household head	0.8962	0.09315	-2.598	0.8962	0.09315	-2.598
Father's length of schooling	8.656	18.89	0.08098	8.656	18.89	0.08098
Father's age	38.97	140.1	-0.4676	38.97	140.1	-0.4676
Father is Muslim	0.9465	0.05068	-3.97	0.9465	0.05068	-3.97
Father is self-employed	0.4104	0.2423	0.3644	0.4104	0.2423	0.3644
Father is government worker	0.08491	0.07782	2.978	0.08491	0.07782	2.978
Father is private worker	0.2563	0.1909	1.116	0.2563	0.1909	1.116
Father is casual worker	0.1541	0.1306	1.916	0.1541	0.1306	1.916
Mother's length of schooling	8.607	17.34	-0.02639	8.607	17.34	-0.02638
Mother's age	36.92	86.12	1.19	36.92	86.12	1.19
Mother is Muslim	0.9497	0.04786	-4.114	0.9497	0.04786	-4.114
Mother is self-employed	0.2343	0.1797	1.255	0.2343	0.1797	1.255
Mother is government worker	0.1226	0.1078	2.301	0.1226	0.1078	2.301
Mother is private worker	0.05189	0.04927	4.041	0.05189	0.04927	4.041
Mother is casual worker	0.5283	0.2496	-0.1134	0.5283	0.2496	-0.1134
Industry employment growth	0.004915	0.004172	0.9483	0.004915	0.004172	0.9483
Use electricity	0.9843	0.0155	-7.786	0.9843	0.0155	-7.786

Table A11: Before weighting (Kelud sample)

	Treatment			Control		
	Mean (1)	Variance (2)	Skewness (3)	Mean (4)	Variance (5)	Skewness (6)
Gender	0.4804	0.2503	0.07827	0.5355	0.2492	-0.1422
Age	8.469	3.662	0.2958	8.289	3.172	0.4547
Urban	0.4972	0.2507	0.01117	0.6011	0.2402	-0.4128
Household size	8.958	6.175	1.257	9.144	8.052	1.187
Gender of household head	0.8994	0.0907	-2.656	0.8812	0.1049	-2.356
Father's length of schooling	8.469	17.27	-0.1048	7.849	17.41	0.05004
Father's age	39	125.5	0.139	38.87	177.5	0.1135
Father is Muslim	0.9777	0.02191	-6.463	0.9167	0.07652	-3.015
Father is self-employed	0.3436	0.2262	0.6588	0.2926	0.2073	0.912
Father is government worker	0.03911	0.03768	4.755	0.08333	0.07652	3.015
Father is private worker	0.3296	0.2216	0.725	0.2801	0.202	0.9792
Father is casual worker	0.1676	0.1399	1.78	0.2199	0.1718	1.353
Mother's length of schooling	8.271	12.21	0.2203	7.443	16.58	0.1633
Mother's age	35.84	64.13	0.9473	35.94	78.85	0.8966
Mother is Muslim	0.9777	0.02191	-6.463	0.9149	0.078	-2.974
Mother is self-employed	0.176	0.1454	1.702	0.1826	0.1495	1.643
Mother is government worker	0.03352	0.03249	5.183	0.03901	0.03755	4.762
Mother is private worker	0.1732	0.1436	1.727	0.1543	0.1307	1.914
Mother is casual worker	0.5503	0.2482	-0.2021	0.5762	0.2446	-0.3086
Industry employment growth	0.05459	0.004684	0.6088	0.03998	0.006269	0.696
Use electricity	0.9972	0.002793	-18.84	0.9929	0.007054	-11.75



Table A12: After weighting (Kelud sample)

	Treatment			Control		
	Mean (1)	Variance (2)	Skewness (3)	Mean (4)	Variance (5)	Skewness (6)
Gender	0.4804	0.2503	0.07827	0.4805	0.2501	0.07804
Age	8.469	3.662	0.2958	8.469	3.661	0.2966
Urban	0.4972	0.2507	0.01117	0.4972	0.2504	0.01114
Household size	8.958	6.175	1.257	8.958	6.174	1.257
Gender of household head	0.8994	0.0907	-2.656	0.8993	0.09071	-2.654
Father's length of schooling	8.469	17.27	-0.1048	8.469	17.27	-0.1045
Father's age	39	125.5	0.139	38.99	125.5	0.1396
Father is Muslim	0.9777	0.02191	-6.463	0.9776	0.02191	-6.459
Father is self-employed	0.3436	0.2262	0.6588	0.3439	0.226	0.6574
Father is government worker	0.03911	0.03768	4.755	0.03914	0.03767	4.753
Father is private worker	0.3296	0.2216	0.725	0.3299	0.2215	0.7235
Father is casual worker	0.1676	0.1399	1.78	0.1678	0.1399	1.778
Mother's length of schooling	8.271	12.21	0.2203	8.27	12.21	0.2208
Mother's age	35.84	64.13	0.9473	35.83	64.12	0.9482
Mother is Muslim	0.9777	0.02191	-6.463	0.9776	0.02191	-6.459
Mother is self-employed	0.176	0.1454	1.702	0.1762	0.1454	1.7
Mother is government worker	0.03352	0.03249	5.183	0.03354	0.03248	5.181
Mother is private worker	0.1732	0.1436	1.727	0.1734	0.1436	1.725
Mother is casual worker	0.5503	0.2482	-0.2021	0.5501	0.2479	-0.2016
Industry employment growth	0.05459	0.004684	0.6088	0.05459	0.004684	0.609
Use electricity	0.9972	0.002793	-18.84	0.9972	0.002794	-18.83

### D.3 Combination of matching and triple difference estimation

Table A13 presents the results of stacked data estimation under the PSM and entropy matching techniques. We find that the results are consistent across the two matching procedures. All effects are still negative and statistically significant. The treatment effects using the PSM method balanced sample (column 2) and entropy balancing sample (column 3) have similar coefficients to the initial unmatched sample. This suggests that our result is not biased by time-invariant covariate imbalances.

Table A13: Matching method and triple difference

	Dep. variable: School enrollment		
	Unmatched (1)	PSM (2)	Entropy (3)
$Treat_{ist} \cdot Post_t \cdot Distance_{ist}$	-0.00119** (0.000537)	-0.00114** (0.000551)	-0.00113* (0.000651)
Child's covariates	✓	✓	✓
Parent's covariates	✓	✓	✓
Area's covariates	✓	✓	✓
Subdistrict's latitude and longitude	✓	✓	✓
Time fixed effect	✓	✓	✓
Individual fixed effect	✓	✓	✓
Obs.	3,987	3,949	3,949
Adj. R2	0.0682	0.0337	0.0809

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$