WINPEC Working Paper Series No.E2006
June 2020

Impacts of Natural Disaster on Changes in Parental and Children's Time Allocation: Evidence from the Great East Japan Earthquake

Shuhei Kaneko, Haruko Noguchi

Waseda INstitute of Political EConomy
Waseda University
Tokyo, Japan

Impacts of Natural Disaster on Changes in Parental and Children's Time Allocation: Evidence from the Great East Japan Earthquake*

Shuhei Kaneko†, Haruko Noguchi‡

Abstract

While recent studies have documented that parents' and children's own time investment are crucial factors of cognitive and non-cognitive development, the causes of changes in their (endogenous) choices are understudied. Exploiting the regional variation of the Great East Japan Earthquake (the Earthquake) and applying difference-in-differences, we present new and robust evidence that a disastrous shock can lead to a positive time investment in children's development by both parents and children. On the other hand, parental monetary investment was negatively affected by the Earthquake. This observation suggests the existence of replacements between pecuniary and nonpecuniary parental investment. Interestingly, the positive effects in children's own studying time are more intensive among children of less-educated mothers and children not enrolled in cram schools: the population which might not have a rich studying environment.

---

† Shuhei Kaneko (corresponding author) is a graduate student at Graduate School of Economics, Waseda University, 1-6-1 Nishi-Waseda, Shinjuku, Tokyo 169-8050 Japan. E-mail: shuhei7700@ruri.waseda.jp.
‡ Haruko Noguchi is a professor at Faculy of Political Science and Economics, Waseda University, 1-6-1 Nishi-Waseda, Shinjuku, Tokyo 169-8050 Japan.

Shuhei Kaneko and Haruko Noguchi appreciate the valuable help and comments from Yoko Ibuka, Yuta Toyama, Hideo Owan, Takuya Hasebe, Fumio Ohtake, the seminar participants of the 14th annual Japan Health Economics Association meeting, 2019 autumn meeting of the Japan Economics Association, and Sophia University. The gratitude also goes to Masato Oikawa and Cheolmin Kang for their advice on data curation. The views and opinions expressed in this article by the independent authors are provided in their personal capacity and are their sole responsibility. All remaining errors are our own. Data used in this study cannot be shared publicly because of Article 33 of Japan's Statistics Act (Act No. 53 of 2007). Data are available based on the criteria set by the Ministry of Health, Labour, and Welfare (contact via https://www.mhlw.go.jp/toukei/sonota/chousahyo.html) for researchers.

Haruko Noguchi appreciates the financial supports by several funds: the Waseda University Research Initiative entitled "Empirical and theoretical research for social welfare in sustainable society- Inheritance of human capital beyond 'an individual' and 'a generation'"—(PI: Haruko Noguchi) and a Grant-in-Aid for Scientific Research Project funded by the Ministry of Health, Labour, and Welfare (MHLW): "Effects of the prevention policy of lifestyle-related disease on labor productivity and the macro economy from the viewpoint of cost-effective analysis" (PI: Haruko Noguchi). This study has received official approval for the use of secondary data from the Statistics and Information Department of the MHLW under Tohatsu-0507-3 as of May 7, 2018, and this research was conducted with permission from the Ethics Review Committees of Waseda University (approval no. 729-420). Shuhei Kaneko and Haruko Noguchi have declared that no competing interests exist.

Keywords: Parental Labor Supply; Parental Time Allocation; Children's Time Allocation; Earthquake; Natural Disaster; Japan

JEL codes: J13**;** J22; J24

Highlights

- We investigate the effect of natural disasters on time invested in child development.
- We find a relationship between natural disasters and changes in time allocation.
- Parents compensate for low monetary investment by increasing their time investment.
- Changes in children's time allocation for educational purposes are heterogeneous.
- Girls and children of less educated mothers are more likely to study for longer.

1. Introduction

The formation of human capital has been one of the most important issues in the realm of labor economics since Becker (1962) pioneered the field. Subsequent previous studies found that early- and middle-childhood skill formation and living environments are crucial factors in predicting the gaps in wage, education, and adulthood health (Currie 2009; Almond and Currie 2011).Therefore, researchers have examined how children's cognitive, health, and non-cognitive outcomes are formulated and affected by parental investments. Among the myriad factors found, many studies have shown that time investment is one of the most crucial inputs for children's skill formation.

For instance, Heckman (2006) and Cunha and Heckman (2007) have shed light on the importance of the early childhood environment. Cunha and Heckman (2008) indicate that the inputs in early childhood are more effective for cognitive skills, while the inputs in later ages have a greater effect on non-cognitive skills.[1] Attanasio et al. (2015) also emphasize the importance of parental investment for childbearing during infancy[2]: their results imply that parental investment in early childhood has significant effects on the cognitive development and health of children.

[1] Cunha and Heckman (2008) explored many parental investment variables (home input measures) in Children of the National Longitudinal Survey of Youth, 1979, to construct low dimensional latent variables. You can see the details of the raw variables of this data in Todd and Wolpin (2007).
[2] The parental investment factor is based on a number of expenditures parents made, including purchases of books and stationery, clothing, shoes, and uniforms.

Regarding the role of parental time investment, Del Boca et al. (2014) state that parental time investment plays a crucial role in children's cognitive skill formation especially in early childhood, and they find that the relative importance of time investment to pecuniary investment decreases as the children grow up. Furthermore, Del Bono et al. (2016) estimate the relationship between maternal time allocation for children and children's outcomes. They show that early maternal time inputs have strong long-term effects on cognitive skill development. Carneiro and Rodriguez (2009) obtain the same results by using the generalized propensity score.

Another strand of research compares the efficiency of parental time investment and time spent in childcare (e.g., kindergarten or pre-school) (Gupta and Simonsen 2010; Yamaguchi et al. 2018; Fort et al. 2020 among others).[3] The series of these studies implies that the relative efficiency of parental investment, compared to childcare enrollment, is determined by its quality: if parents can provide *high quality* (pecuniary or non-pecuniary) investment in their children's development, then childcare does not necessarily play an important role in developing children's skill.

[3] Gupta and Simonsen (2010) found that being enrolled in preschool, where the children can interact with highly qualified staff members at age three is as good as home care (provided by parents) for child outcomes at age seven regardless of the child's gender or the mother's level of education by using Danish data. On the other hand, family day care seems to reduce the non-cognitive abilities of boys born to mothers with low levels of education. This finding is confirmed by a study in a Japanese setting. Yamaguchi et al. (2018) report some advantages of childcare, showing that being enrolled in childcare improves language development among boys and reduces aggression and the symptoms of attention-deficit hyperactivity disorder (ADHD) among the children of less educated mothers. Conversely, Fort et al. (2020) report that children enrolled in kindergartens are likely to suffer from poorer cognitive outcomes and the deterioration becomes more critical if the household income is higher.

Compared to the researches investigating the role of *parental* time investment, little is known about the importance of children's *own* time investment (Del Boca et al. 2014; Fiorini 2010; Fiorini and Keane 2014; Borga 2019). However, while the number of such studies is limited, their conclusions seem to be consistent. For instance, Fiorini and Keane (2014) find that children's time allocation to educational activities, particularly with parents, is the most productive input for cognitive skill development. On the other hand, their study implies that non-cognitive skills appear insensitive to alternative time allocations, but they are affected by the mother's parenting style. Del Boca et al. (2017) compare the effect of children's own and parental time investment. By applying two types of fixed effects (sibling and individual), they show that the time investment made by children during their adolescence affects their cognitive test scores more than that made by mothers after controlling for potential endogeneity. The consistent conclusion of these studies is that children's own time investment is important for cognitive skill formation, while the evidence is mixed regarding non-cognitive skills.

While quite a few studies have investigated the effects of time inputs for children's (cognitive and non-cognitive) skill development, with almost all of them reaching the conclusion that time input is one of the most crucial factors, how children and parents determine their time allocation or what kind of events can change time allocation remain understudied. One of the exceptions is a study estimating the impact of weather conditions on children's activities. Nguyen et al. (2019) show that unfavorable weather conditions such as cold or hot temperatures or precipitation lead children to switch activities from outdoors to indoors, mainly by reducing the time allocated to outdoor activities and travel and increasing the time allocated to media.

Our study can contribute to another strand of studies: the relationship between natural disasters and their consequences on children and households. Many economic studies have examined the impacts of natural disasters on health status (Chen and Zhou 2007; Currie and Rossin-Slater 2013[4]), risk preferences (Cameron and Shah 2015; Hanaoka et al. 2018), altruism (Li et al. 2013), economic growth (Skidmore and Toya 2002; Loayza et al. 2012; Cavallo et al. 2013) and so on. However, its impacts on time allocation among the affected population is not well scrutinized due to the inadequacy of data or endogeneity problems. Although this study does not directly estimate the effects on cognitive and non-cognitive skills, the findings are still important in the sense that it sheds light on the novel mechanism of time investments in children's development.

In this study, to evaluate the impact of a negative shock on parental and children's time investment during childhood, we use the Great East Japan Earthquake (the Earthquake, hereafter) of 2011 as a natural experiment. Further, we try to explain its heterogeneity and

[4] Chen and Zhou (2007) find that the impact of being exposed to serious famine (the Great Chinese Famine 1959–61) in early childhood negatively affects long-term health outcomes. Currie and Rossin-Slater (2013) find that exposure to a hurricane during pregnancy increases the probability of abnormal conditions of the newborn babies.

investigate possible concerns in the estimation. The regional variation in the degree of the seismic intensity is used to construct a Difference-in-Differences (DID) estimation. Our findings can be summarized as follows. Firstly, we show robust and unique evidence that a disastrous shock can lead to a positive time investment in children's development not only by the parents but also by the children. Secondly, we suggest that this increase in parental time investment can be explained by the need to compensate for shortages in pecuniary investment. Thirdly, as opposed to previous studies (e.g., Dearden et al. 1997), surprisingly, the increase in children's own time allocation for educational activity is mainly derived from girls and children of low-education mothers.

The remainder of the paper is organized as follows. The next section introduces the description of the data. Section 3 presents the framework of the empirical study and provides the identification strategy to estimate the effect. Section 4 explains the empirical results. Finally, Section 5 discusses the results, derives implications, and concludes the paper.

2. Data and Variables

To investigate the effect of a natural disaster on various behaviors and outcomes of children and their parents, the following two datasets are compiled: (A) seismic intensity and (B) parental and children information.

2.1 Seismic Intensity

Japan has experienced serious earthquakes in the last few decades: the Great Hanshin-Awaji Earthquake in 1995, Niigata Chuetsu Earthquake in 2004, The 2016 Kumamoto earthquakes in 2016 and so forth. Among them, the Earthquake is the largest in the country's history since modern measurements of earthquakes were established; it is the fourth largest earthquake on record in the world in terms of the moment magnitude (Mw). The Earthquake occurred at 2:46 PM on March 11, 2011, triggering a tsunami that hit coastal areas in the northeastern region of Japan (mainly Iwate and Miyagi prefectures), which caused 15,897 deaths and 2,532 disappearances as at June 10, 2019 (National Police Agency 2019). In addition to the number of victims and property damage, the Earthquake was highly devastating in multiple dimensions. For instance, soon after the Earthquake occurred, the Fukushima Dai-ichi nuclear power plant, which is located close to the Pacific Ocean and 180 km away from the epicenter, experienced failures in the cooling systems of its reactors (Rehdanz et al. 2015). This resulted in the release of large amounts of toxic radioactive materials into the air, forcing nearby households to evacuate.

Because of this accident, the power supply by the Tokyo Electric Power Company (TEPCO) was reduced by 21 GW (Okada et al. 2011), resulting in 4.66 million households experiencing an electric outage for several days in six prefectures located in Tohoku region.[5] Furthermore, a rolling blackout was implemented in some areas from March 14 to March 28 to compensate for the electric shortage.

The damages caused by the Earthquake were highly variant between different regions in Japan. People living in the northeastern area (especially in the coastal area and close to Fukushima Dai-ichi nuclear power plant) experienced serious negative shocks, while people living in western Japan did not suffer from any serious damages. As the research objective of this study is to investigate the effect of the natural disaster on parents and children's behaviors and outcomes, we exploit the variation in the level of damages caused by the Earthquake as the intensity of the "treatment." We utilize the seismic intensity measurement (*Shindo*, in Japanese) as a variable indicating the intensity of the Earthquake. *Shindo* is a measurement constructed by the Japanese Meteorological Agency (JMA), which manages more than 4,000 seismological stations in Japan. The distribution of seismological stations is shown in Figure 1; Table 1 lists the general description of each *Shindo* level in terms of property damage and human perception.[6]

[Figure 1]

[5] http://www.bousai.go.jp/kaigirep/chousakai/tohokukyokun/9/pdf/sub2.pdf (in Japanese, accessed on March 4, 2020)

[6] Table 1 is based on the information available at https://www.jma.go.jp/jma/kishou/know/shindo/kaisetsu.html and Table 1 in Hanaoka et al. (2018). The measurement is classified by the Japan Meteorological Agency seismic intensity scale. Please see https://en.wikipedia.org/wiki/Japan_Meteorological_Agency_seismic_intensity_scale (Accessed in March 9, 2020) for more information.

[Table 1]

Shindo is well known among Japanese people as an index of seismic intensity (Hanaoka et al. 2018). We define a municipality-level treatment variable as the observed maximum *Shindo* in each municipality. For example, if there are three seismological stations in municipality m and the recorded *Shindo* of each station was 3.5, 3.6, and 4.2, then the treatment intensity of this municipality is 4.2.[7] Based on this criterion, we classify all municipalities into control and treatment group as follows: the municipalities fall into the control group if their observed (maximum) intensity is lower than 5.5, while the treatment group consists of municipalities whose intensity is equal to or more than 5.5 (equivalent to *Shindo* 6 or higher). Considering that almost all the victims are from places recording an index of *Shindo* 6 or higher[8], the definition of the treatment group should be justified.

[Figure 2]

The number of deceased or missing people in each municipality might be another possible treatment variable. However, following Hanaoka et al. (2018), we use the seismic intensity (*Shindo*) measured by the common criteria as a treatment variable, mainly because the number of human victims would be endogenous to some characteristics of municipalities,

[7] The results remain qualitatively unchanged if we use the average intensity as treatment variable. (Results are not shown, but available upon request.)
[8] Over 90% of the deaths were caused by the tsunami in this Earthquake (Nikkei 2011). The regions hit by the tsunami, mainly in Iwate, Miyagi, and Fukushima prefecture, are highly correlated with the municipalities with *Shindo* 6 or larger.

such as the degree of precautionary investment and/or social capital.[9,10]

2.2 Parental and Children Information

We use the Longitudinal Survey of Newborns in the 21st Century (LSN21). This is a nationally representative longitudinal survey conducted by the Ministry of Health, Labour and Welfare (MHLW) in Japan. The first survey was conducted in 2001, which surveyed 23,421 (all) children who were born between January 10–17 (*January cohort*) and 23,589 (all) children born between July 10–17 (*July cohort*).[11] The children have been annually followed, and the data was available from the 1st (2001) through to the 15th (2016) survey at the time of receiving official approval for the use of secondary data from the Statistics and Information Department of the MHLW as of May 7, 2018.

The response rates of the first survey are 88.0% and 87.5% for *January* and *July cohorts*, respectively. The attrition rates are around 10% in each subsequent survey. The response rates are much higher than that of similar data collected in other countries. (e.g., National

---

[9] Further, the number of deaths or missing cases has been revised many times; therefore, we need to choose an arbitrary time point to conduct our empirical analyses if we apply this information as a treatment, which would cause an unnecessary manipulation.

[10] Please see Aldrich and Sawada (2015) for the relationship between the number of victims and the quality or quantity of social capital in each municipality.

[11] Children born during May 1–24, 2010 were newly added to LSN21 as the second wave; however, we do not utilize this sample because we exploit the Earthquake that occurred in March 2011 as a natural experiment, which indicates that it is impossible to check the parallel trend assumption before the Earthquake among this cohort. In addition, the detailed questionnaire about children's behavior was not used in this wave.

Longitudinal Survey of Children and Youth (NLSCY), which was conducted in Canada and employed by Baker, Gruber, and Milligan (2008); Currie and Stabie (2003) and so on). While the cumulative response rate in the original cohort is 52.7% after the 8th round was completed in NLSCY[12], the response rate for LSN21 after the 15th survey is still over 60%.

The timing of the survey is slightly complicated. The first surveys for the two cohorts were conducted when the children were 6 months old, and they were followed-up about 6 months after their birthdays each year until the sixth survey; therefore, the surveys were conducted when the children were $n - 0.5$ years old if $1 \leq n$ (wave of the survey) ≤ 6. However, from the seventh survey[13], follow-ups have been conducted around the children's birthdates, so that the children's ages at the timing of each survey is n if $n \geq 7$. The simple structure of LSN21 can be found in Figure 3, based on a figure in Sata et al. (2017).

[Figure 3]

The surveys are continuously conducted for households unless they do not respond twice in a row. Therefore, even if a household missed a survey in a year, the questionnaire would be sent in the following year. In other words, the information on some households that did not respond just after the Earthquake is still available if the households responded a year later.

---

[12] http://www23.statcan.gc.ca/imdb-bmdi/document/4450_D2_T9_V4-eng.pdf (accessed in February 21, 2020)

[13] In summary, the surveys were conducted in August and February for the *January* and *July cohorts*, respectively, until the sixth survey. Then, for each cohort from the seventh to the latest one the surveys were conducted in January and July.

Arguably, such a survey design of LSN21 would avoid serious attrition bias.

In this study, we use the *July cohort* for the following reasons. Firstly, because knowing the immediate effect is one of the important tasks of this study, the *July cohort* (surveyed after 4 months from the Earthquake) is more suitable for this purpose. Secondly, as we explain later, we cannot warrant the parallel trend assumption before the shock for an outcome variable, which suggests that the control and treated units in the *January cohort* may not be balanced. Thirdly, if we used the *January cohort*, the periods after the Earthquake starts from the 11th survey, suggesting that the number of periods we can trace the effect is less than those of the *July cohort*.[14]

2.3 Parental Time Allocation

To investigate the effect of the Earthquake on the changes in parental time use, we derive some measurements from LSN21. Firstly, as several studies have found that employment status highly deteriorated after a natural disaster (Coffman and Noy 2012; Sugano 2016), we estimate the impacts on the decision about the parental labor supply, by a dichotomous variable which takes the value of 1 if each parent is working and 0 otherwise.

[14] We note that the *January cohort* is used just for the sensitivity analyses shown in appendix (see Table A1).

Secondly, according to a simple labor economics theory that outlines a trade-off between working hours and leisure time and/or time spent with children, we examine how the Earthquake would affect the tradeoff. For example, Halla and Zweimüller (2014) found that maternal labor supply was restrained, and instead, the amount of time spent with children increased among families with high socioeconomic status as compensation behavior if the negative shocks (Chernobyl accident) occurred while children are in utero. Furthermore, we would argue whether the time investment in children's development increased after the Earthquake. Even if the labor force participation decreased, it does not directly indicate the increase in time spent with children. To investigate this mechanism as Halla and Zweimüller (2014) did, we exploit an additional question in LSN21 as an outcome variable; asking whether the child basically spends time with household members after school[15], which we utilize as a proxy of intra-household communication. If the mechanism exists, the probability of answering "yes" to the above question should increase in the devastated areas after exposure to the shock.

2.4 Children's Own Time Allocation

[15] The questionnaire asks, "With whom does the child spend time after school until about 6 pm?". The possible answers were (i) alone, (ii) with friends, (iii) cohabiting family members (including parents and grandparents), (iv) non-cohabiting family members, (v) adults other than the family members, and (vi) others. We generate a dummy variable taking one if the answer to (iii) is yes.

Many recent studies focusing on children's own time allocation exploit the time use diary data which document how much time the children spend, on what types of activities, and with whom (Fiorini and Kaene (2014); Nguyen et al. (2019); Del Boca et al. (2014, 2017); Caetano (2015); Caetano et al. (2019)).[16] Del Boca et al. (2017) estimate the impact of children's own time investment on cognitive and non-cognitive outcomes and compare the magnitude of these investments with that from parents. Caetano et al. (2019) applied a test of exogeneity developed in Caetano (2015) to search for models that yield causal effects of children's time allocation on their cognitive skill development.

However, LSN21 does not include a detailed time-use diary. Instead, we exploit the questionnaire, asking, "How many hours does the child study, play video games, and watch TV, per day on weekdays?" The respondents answer these questions by categorical variables.[17] For the simplicity of estimation, we generate a dummy variable that takes the value of 1 if the child spends more than 1 hour for each activity per day and 0 otherwise. Also, following the suggestion by Caetano et al. (2019), we consider the bunching at zero

[16] Fiorini and Kaene (2014) and Nguyen et al. (2019) used the Longitudinal Study of Australian Children (LSAC) in which children's activities are reported according to the 96 15-minute periods per day. The structure of this study enables researchers to accurately capture the time spent on each activity and estimate the substitution or trade-off between them. Another popular dataset among the related literature is the Child Development Supplement (CDS) of Panel Study of Income Dynamics, where all activities during the day (including its duration and location) and who else (if anyone) participated in these activities are recorded (Del Boca et al., 2014).

[17] For studying time, the choice set was as follows. 1 if not at all, 2 if less than 30 minutes, 3 if 30 minutes to 1 hour, 4 if 1 to 2 hours, 5 if 2 to 3 hours, 6 if 3 to 4 hours, 7 if 4 to 5 hours, and 8 if more than 5 hours. Regarding time spent playing games and watching TV, the choice set was as follows. 1 if not at all, 2 if less than 1 hour, 3 if 1 to 2 hours, 4 if 2 to 3 hours, 5 if 3 to 4 hours, 6 if 4 to 5 hours, 7 if 5 to 6 hours, and 7 if more than 6 hours.

minutes[18] and construct another dummy variable which takes the value of 1 if the child spends some (non-zero) time for each activity per day and 0 otherwise.

3. Empirical Strategy

Our main identification strategy relies on the exogeneity of the seismic intensity and we apply DID estimation. Firstly, DID requires the common trend assumption to be met for ensuring the internal validity of the estimation results. It means that the transitions of the outcomes of our interests between treatment and control groups before the Earthquake are necessary to be parallel over time (Angrist and Pischke, 2008). We use event study analysis to check this assumption as follows (Autor, 2003),

$$(1)\quad Y_{imt} = \beta_0 + \sum_{\substack{k \in P \\ k \neq 9}} \beta_{1,k}\ I(t = k) + \ \beta_2 Treatment_m + \sum_{\substack{k \in P \\ k \neq 9}} \beta_{3,k} * I(t = k) * Treatment_m + \boldsymbol{\gamma X}_{imt} + \theta_i + \epsilon_{imt},$$

where Y_{imt} is the outcome variable of individual i living in municipality m at the period t, including the parental labor force participation, parental pecuniary (non-pecuniary) investment, and children's own time allocation (explained in Section 2.3 and 2.4). $I(t = k)$

[18] The intuition behind this paper is the following. Consider the time spent on reading books, for instance. Children that perform this activity for 60 minutes a day should be similar to the children that spend 45 minutes a day. Furthermore, the children that perform this activity for 45 minutes a day should share similar characteristics with the children that spend 30 minutes a day, and so on. However, the notion of this similarity is violated at the point of zero minutes. Due to the non-negative restriction of time, when they choose to spend zero minutes in this activity, it is possible for them to choose a "corner solution": they may desire to choose negative amounts of that input but cannot. Therefore, the unobserved characteristics of children are highly likely to be discontinuous at zero minutes' point.

is an indicator variable, taking 1 if the survey was conducted in kth period. $Treatment_m$ takes 1 if the individual i lives in a municipality classified under the treatment group, where the classification of the seismic intensity level is introduced in Section 2.1 and individuals living in the area of the lower-intensity level (*Shindo* 0 to 5.5) are categorized into control the group[19]. $\boldsymbol{X}_{imt}$ is a vector of characteristics of individual i, including the number of siblings, whether the child lives with grandparents, their height, weight, and prefecture dummy variables. The term θ_i represents the unobserved time-invariant individual fixed effect[20], and ϵ_{imt} is an unobservable random shock. In estimating Equation (1), we employ only the *July cohort*. The coefficient $\beta_{1,k}$ captures the time trends in period k, which commonly affect entire samples. β_2 estimates regional fixed effects based on the seismic intensity. $\beta_{3,k}$ measures the difference in the effects of the event on people living in "treated" municipalities from the control group in period k, which is the main interest of our study. Because we consider the Earthquake (occurred between 9th and 10th survey) as the exogenous shock to entire samples, $\beta_{3,k}$ should not be different from zero if $j \leq 9$ (parallel trend assumption before the shock)[21]. If this assumption is satisfied, we can assume that $\beta_{2,k}$ represents the *causal effect* of the Earthquake when $j \geq 10$. A critical limitation of LSN21 is that the

[19] In the latter section, we try the different definition of control groups as a sensitivity analysis.
[20] In all the regressions, the results of Hausman test and F-test justify the adoption of Fixed Effect model.
[21] When we try the same regression for the *January cohort*, this assumption is violated in maternal labor force participation. As we stated in Section 2.2, this is one of the reasons we do not utilize the *January Cohort* in our study. Table A1 shows the result for the sensitivity test when we include the *January cohort* in our estimation. We set $After_t$ being equal to 1 if $t \geq 11$ (see Equation (2)).

questions are not consistent across survey years, which causes us to use a limited number of covariates in different time windows for each outcome variable. The notation P in Equation (1) indicates that the data is available; in other words, the summed survey periods depend on data availability.[22]

After we confirm if common trend assumptions are met for the outcome variables, we conduct the DID, for which the estimated equation reduces from (1) to

(2) $Y_{imt} = \beta_0 + \beta_1 After_t + \beta_2 Treatment_m + \beta_3 After_t * Treatment_m + \boldsymbol{\gamma X}_{imt} + \theta_i + \epsilon_{imt},$

where $After_t$ takes 1 when $t \geq 10$ holds. The parameter of interest in Equation (2) is β_3.

Then, we investigate the heterogeneity in the impacts. To this purpose, we implement the DID dividing the sample by the child's gender and parental (maternal) educational attainment. We estimate the following equation:

(3) $Y_{imt} = \beta_0 + \beta_1 After_t + \beta_2 Treatment_m + \beta_3 After_t * Treatment_m + \beta_4 Z_i * After_t$

$$+ \beta_5 Z_i * Treatment_m + \beta_6 Z_i * After_t * Treatment_m + \boldsymbol{\gamma X}_{imt} + \theta_i + \epsilon_{imt}.$$

where the coefficient β_6 is interpreted as the difference based on the characteristic Z_i, which are children's gender (dichotomous variable taking the value of 1 if the child is a girl and 0 otherwise), maternal educational attainment (dichotomous variable taking the value of 1 if the mother's educational attainment is higher than high school graduate and 0 otherwise),

[22] For instance, the parental labor force participation is available from the second to the fifteenth survey periods (i.e., $2 \leq P \leq 15$), while we can see the proxy of parental time allocation to children only from the seventh to the eleventh survey (i.e., $7 \leq P \leq 11$).

or whether the child goes to cram school (proxy of studying environment). Our concerns are the p-value of β_6. If β_6 is estimated to be statistically significant, there would be heterogeneity in the impacts by the child's gender and maternal educational attainments.

4. Results

4.1 Descriptive Evidence

As an initial investigation, we show simple descriptive statistics of each outcome variable dividing the entire sample into the control and treated groups. Figure 4 reports the trajectory of parental time allocation variables (defined in Section 2.3).

[Figure 4]

Panel A shows that maternal labor force participation among treated families was reduced by approximately 5 percentage points after the Earthquake, while paternal labor force participation was unaffected. Furthermore, time trend (e.g., the slope) before the event is quite parallel in control and treated groups for both variables.

Panel B indicates that the probability of children spending time with household members after school increased after the Earthquake in the treatment group compared to the control group. This result suggests that parents (or grandparents) tend to spend more time with children after experiencing a shock. Combined with the results in panel A, we can infer that the increase in time allocation was mainly derived from mothers rather than fathers; after mothers quit their job, they seem to stay with their children at home.

[Figure 5]

In the same way, Figure 5 shows the trajectory of children's own time allocation variables (defined in Section 2.4). We should note that the assumption of the parallel trend before the event seems to be satisfied in all variables. Panel A indicates that the time devoted to studying was increased among the treated children since the eleventh survey point. In panel B, the trends before and after the Earthquake are almost the same in both groups, which implies an insignificant effect of the Earthquake on time spent on playing games. Panel C suggests that children among treated regions are less likely to spend their time watching TV after the shock compared to the children in control regions.[23] In sum, there would be a substitution of time allocation from exposure to media (e.g., watching TV) to educational activity (e.g., studying) after experiencing the Earthquake.

4.2 Event Study (Test for Parallel Trend)

Figure 6 and 7 show the results of the event study associated with Equation (1), where

[23] We exclude the information of children's time allocation for playing video games and watching TV in the tenth survey because we detect a serious sample attrition in some questions asked in this survey (i.e., the sample size is approximately 1/8 compared to the other surveys). In the appendix, we show the results of DID including this survey period; however, overall results are consistent with main analyses because of the small sample size. Please see Table A2.

we set the 9th survey (just before the Earthquake) as a reference to compare the trends of the control and treatment groups.

[Figure 6 and 7]

For all outcomes, we find that the coefficients are statistically insignificant before the Earthquake, which suggests that the parallel trend before the event seems to be sufficiently satisfied. Figure 6 shows that the maternal LFP was significantly and drastically reduced after the Earthquake, and this effect is persistent. The time spent with their children has been increasing continuously and the effect becomes significantly positive at the 12th survey period. Panel A of Figure 7 indicates that the children's time allocation to studying starts increasing by the 11th period (not *just* after the Earthquake). On the other hand, the coefficients in time spent for playing video games and watching TV are not statistically significant after the Earthquake. Most importantly, the results of event analyses confirm visually that common trend assumptions are met for all outcomes for ensuring the internal validity of the DID estimates.

4.3 DID

[Table 2]

Table 2 documents DID estimates by Equation (2) for the effect of the Earthquake on the changes in parental time allocation variables. As expected from the descriptive statistics, we find a drastic reduction in maternal labor force participation by 6.2 percentage points (or 10.8 from the averaged mean outcome) after we utilize some control variables and prefecture fixed effects among families living in the devastated region. Surprisingly, we can observe significant positive effects on paternal labor force participation by 0.6 percentage points; however, considering that almost all fathers work (98.8% on average), we could conclude that the effects are negligible. With regard to the variable of whether the child spends time with household members after school, we see a significant positive coefficient among treated households at the 10% significance level, where the magnitude is 2.8 percentage points (or 3.9% based on the averaged value).

[Table 3]

Table 3 reports the effects of the disaster on children's own time use. The table shows that, in this regard, the Earthquake's impact was in different forms. (i) While the estimate is not sufficiently precise, the probability of studying more than 1 hour per weekday increased by 2.0 percentage points, and (ii) children living in damaged areas were more likely to spend some (non-zero) time per weekday for studying than those in non-damaged regions by 2.0 percentage points (see columns (1) and (2)). Although the Earthquake does not seem to have had an influence on the time spent playing video games, we observe a significant negative effect on time allocated to watching TV: the probability of children watching TV for more than 1 hour per day on a weekday increased by 3.2 percentage points (or 4.1% from the mean outcome). Thus, the DID estimates are consistent with the results shown by panel A to C in Figure 5. After the shock, children substitute their "leisure" time (exposed to media) to "investment" in their cognitive skills by increasing the time devoted to studying.

4.4 Migration

One possible concern is whether and how migration affects our results. As some households moved to the unaffected regions after the Earthquake, our main results would be underestimated due to the selection bias caused by migration. To test this possibility, we exclude households that moved to different municipalities at least once after the Earthquake and conduct DID. Table 4 shows the results.

[Table 4]

Even after we exclude the migrated households to other municipalities, the results are almost the same as Table 2 and 3, which highlights that the main findings in Section 4.2 are robust to the selective migration. However, it is worth noting that there was a substantial change in the children's time allocation to studying for more than 1 hour per day, shown by column (4). The coefficient increased from 2.0 to 3.3 percentage points and became statistically significant at the 5% level. This might reflect that children who did not migrate were more likely to be restricted from playing or being outdoors after the Earthquake and therefore, tended to stay at home and study more. Households' migration is often treated as "the contamination" when estimating the effects of a policy change. However, in our case, we emphasize that selective migration could help us identify the mechanism of households' behavior (in a euphemistic manner).

[Figure 8]

Besides, the time trend of the probability of moving shown by Figure 8 indicates that it discontinuously increased only in the treated (i.e., damaged) region. Hence, this would support our hypothesis as above.

4.5 Time or Money

Previous literature underlines that time allocation is an important factor in children's skill development and that it should be analyzed alongside the effects of the monetary and/or goods investments for children (e.g., Del Boca et al., 2014; Del Bono et al., 2016; Francesconi and Heckman, 2016). Thus, we also focus on the monetary investment.

[Table 5]

Table 5 summarizes the DID estimation where we take the logarithm of monthly expenditure spent on the children as an outcome variable. The results of Table 5 imply that the mother's income decreased (see column (2)) while the effects on the father's income are negligible (see column (3)).[24] In other words, we can interpret the results of the father's income as a "falsification test."

Furthermore, we observe that the parents' monetary investment in their children's development significantly dropped by about 6.8% in the treatment group after the Earthquake. This decrease in monetary investment can be explained by the 10.8% reduction in the mother's annual income after the shock. On the other hand, the effects on the father's annual income are statistically insignificant and the estimated magnitude is apparently negligible. This would reflect the labor supply results (shown by columns (1) and (2) in Table 2), such that the mother's LFP significantly decreased and the father's LFP was not affected.

From the results in tables 2 and 5, we can shed light on the mechanism behind the parents' behavioral changes. These results imply that many mothers in the damaged area ceased to work after the Earthquake, which hampered them from spending significant amounts of *money* on their children's development. At the same time, however, they became more likely to stay home and spend their *time* with children. In other words, we can interpret that parents increased their time investment to compensate for limited pecuniary investment.

[24] We take the logarithm of parental income to interpret the results in Table 5 consistently.

4.6 Heterogeneous Effect[25]

4.6.1 Heterogeneity Based on Child's Gender

Table 6 documents the difference in the estimated results by the child's gender associated with Equation (3). Panel A and B show the samples of boys and girls, respectively.

[Table 6]

Column (1) shows that maternal LFP after the Earthquake sharply decreased by 7.2 percentage points for girls and 5.2 percentage points for boys. However, we find the difference between boys and girls statistically insignificant (p-value of β_6 equals to 0.426). We should note that the maternal LFP is not determined solely by characteristics of the surveyed child, but also by other factors in the household such as the total number of older or younger siblings and the grandparents' ability to help with childcare daily. In addition, concerning the children's own time allocation, we find a robust trend that girls tended to substitute their time watching TV with studying after the Earthquake. However, we do not observe statistically significant differences across the child's gender (in that p-values of β_6 is larger than 0.1). Interestingly, we find a significant difference (p-value of β_6 equals to 0.092) in the proxy of parental time allocation by the child's gender, that is, parents were more likely to spend their time with boys rather than girls. Further, the difference in the probability of

[25] The results of event study for subsamples are provided in Figure A1-A6. This analysis shows that the common trend assumption appears to be satisfied in all the subsamples examined.

playing video games for more than 1 hour per day on a weekday is statistically significant between genders (p-value of β_6 is 0.068), while the coefficients are not statistically significant for both genders.

4.6.2 Heterogeneity Based on the Mother's Education

Table 7 summarizes the differences in the estimated results by maternal educational attainments based on Equation (3). Panel A and B show the samples of the "high-education group" and "low-education group," respectively.

[Table 7]

Columns (1) and (3) show that maternal LFP and time allocation for their children were slightly more affected in the families with highly educated mothers than the ones with less educated mothers, though the differences are not statistically significant (p-values of β_6 are 0.732 and 0.311). Regarding children's own time allocation, we observe that both probabilities of studying for more than one hour and some (non-zero) time per day on weekday are significantly more increased in the families with less educated mothers compared to the ones with highly educated mothers. The results are surprising since they are contrary to those of previous studies (e.g., Carneiro et al., 2013). Yet, the statistical significances in the probabilities of studying for "more than 1 hour" and "some (non-zero) time" per day on weekday differ, of which the p-values of β_6 are 0.052 and 0.898, respectively.

4.6.3 Heterogeneity based on Children's Enrollment to Cram Schools (Proxy for the Studying Environment)

For estimating the effects on children's studying behavior, it is important to consider the children's studying environment.

In Japan, some children go to cram schools to prepare for the entrance examinations of (mostly) private junior high schools (generally, when they are 11–12 years old). Therefore, it is entirely possible that whether they go to cram schools is a significant factor that determines the children's studying habits. Table 8 reports the results of this subsample analysis.

[Table 8]

Column (1) indicates that the effects on maternal LFP are stronger if the children go to cram school, although the difference between them is not statistically significant. While the coefficient of column (3) in panel B is not precisely estimated, the magnitude is large (0.098), which is consistent with the larger reduction in maternal LFP.

As we expected, the effects on children's studying behavior is quite heterogeneous. For children not enrolled in cram schools, those who lived in damaged areas were more likely to increase their study time, representing 10.2 percentage points increase in probabilities of studying for more than one hour, and 4.2 percentage point increases in probabilities of studying some time. On the other hand, these effects are not significantly estimated among the children who go to cram schools (i.e., children who have a studying environment).

While we do not find any significant estimates for time spent on video games, the time spent on watching TV decreased in both subgroups. The probability of watching TV for more than 1 hour per weekday decreased by 3.3 percentage points among children not enrolled in cram schools, and the probability of watching TV for some (non-zero) time also decreased by 5.7 percentage points if we consider only the children going to cram schools.

4.7 Sensitivity

4.7.1 Different Control Groups

We classify the municipalities whose maximum *Shindo* during the Earthquake was less than 5.5 as the control group. We compare the treatment group (*Shindo* is more than or equal to 5.5) with different control groups because some areas just below the original threshold would still suffer from damages by the Earthquake or by tsunami especially if they are located near the coastal area. To avoid the ambiguity of the "treatment," we shrink the control group. The idea is that if we compare the treated group (i.e., *Shindo* ≥ 5.5) and the municipalities with less Earthquake intensity, it is more likely to clearly compare the treated region and control region.

Therefore, for the sensitivity of our baseline results, we reduce the size of controlled municipalities whose *Shindo* is from less than 5.5 to (i) 5.0 or (ii) 4.5. On the other hand, the treatment group is the same as in the previous sections. Table 9 shows the results for sensitivity analyses. Panels A, B, and C show the results of baseline ("less than 5.5") and of changing the definition of the control group to "less than 5.0" and "less than 4.5," respectively.

[Table 9]

Table 9 indicates that tightening the threshold of the control group does not influence the overall results significantly, except for the result in column (4). The coefficients are statistically insignificant for panel A, while it became significant at the 5% level for panels B and C, showing that the probability of studying for more than 1 hour would be increased by 2.4 (2.9) percentage points for children living in municipalities with *Shindo* 5.5 and more, compared to those with *Shindo* less than 5.0 (4.5). It is also worth noting that this change occurs with the increase of the magnitude in column (8), indicating the substitution of time spent watching TV with time spent studying.

All these effects can be interpreted as causal effects in terms of the common trend assumption before the event. Please see Figure A7 and A8.

4.7.2 Excluding the Effects of the Nuclear Power Plant Accident

The accident that occurred at the Fukushima prefecture nuclear power plant should also be considered in this analysis. Besides the damages caused by the Earthquake and tsunami, this accident caused serious secondary damages, from the shortages of electricity (Vivoda 2012) to harmful rumors about the residents (Haworth 2013; Managi and Guan 2017). While tsunamis or damages to physical structures are common in earthquakes in other countries (e.g., Northridge Earthquake in 1991 or Sumatra Earthquake in 2004 among others), we note that the nuclear power plant accident is highly peculiar to the Earthquake. To verify the generalizability of this study, we exclude all households located in Fukushima prefecture. Table 10 shows the results.

[Table 10]

According to Table 10, we find almost the same results as the baseline results.

5. Discussion and Conclusion

This study shows that the Earthquake led to a decline in maternal labor supply and an increase in parental time allocation to children in the seriously devastated area. In addition, we find that children's own time allocation to studying increased while their time of watching TV (being exposed to media) slightly reduced after the shock. The results of the event study and several sensitivity analyses validate the causality of our DID identification strategy. At first glance, our results, such that the negative shock (i.e., the Earthquake) would induce positive time investment in educational activity among children in the damaged region, contradicts those of previous studies. For instance, Deuchert and Felfe (2015) explore typhoon Mike that hit Cebu in 1990 and indicate that the exposure to the typhoon caused negative and persistent effects on children's education. In addition, Groppo and Kraehnert (2017) show that the extremely cold winter in Mongolia leads to poorer educational attainment among children, mainly due to losses in household income. However, while these previous studies focus on developing the countries and/or regions whose people are much more vulnerable to the damages, our results reflect the established educational systems and well-functioning disaster preparations in Japan, one of the countries with the highest topographical risk of earthquakes and tsunamis.

Further, we find evidence upholding the hypothesis that the Earthquake induced an increase in parental time investment to compensate for shortages in pecuniary investment. In this regard, we should consider the efficiency of the substitution; that is, does this substitution improve children's cognitive or non-cognitive outcomes? If the importance of time investment is greater than that of monetary investment, the compensation is still valid in terms of the children's skill formation. Unfortunately, however, LSN21 does not have precise information about the children's cognitive outcomes; therefore, we cannot directly answer the question. Nevertheless, we can derive some implications by borrowing the suggestions of past seminal works. For instance, Del Boca et al. (2014) suggest that expenditure on children gains its importance compared to time investment as children grow up. According to their results, pecuniary investment is more effective than time investment for adolescents (the same age range as our targeting population). If that is the case, the substitution of monetary with time investment can deteriorate the affected children's cognitive outcomes in devastated areas compared to the children in non-devastated regions. Hence, we should consider the validity of cash transfers targeted toward the affected households.

Additionally, our subsample analysis indicates that the impact seems to be heterogeneous: girls are more likely to replace their time devoted to watching media with time devoted to studying and children of less educated mothers are more likely to increase their studying time. For example, Carneiro et al. (2013) state that the increase in years of maternal education has substantial positive effects on children's cognitive and non-cognitive development, emphasizing the intergenerational returns of education. Hence, it might have been intuitively more persuasive if we obtained the results that the Earthquake led children with highly educated mothers to study more than those with less educated mothers did. However, our result contradicts those of previous studies.

A similar implication can be derived from the subsample analysis where we exclude the children who are enrolled in cram schools. We find that, after excluding children that attend cram schools, the remaining children are much more likely to spend their time studying.

A possible explanation for this is that children with highly educated mothers study on daily basis regardless of a negative exogenous shock like the Earthquake, while children of less educated mothers or those not enrolled in cram schools (since they possibly studied less) are more likely to start studying for longer or more frequently after the Earthquake. This is probably because unusually significant financial, physical, and human investments by both private and public sectors would expand the budget and time constraints particularly of families with less educated mothers and may contribute to improving children's time allocation in damaged regions after the Earthquake.

There are some limitations and possible extensions of this study. Due to data limitations, we cannot observe the cognitive and non-cognitive skills of children and we cannot fully scrutinize clear mechanisms behind the obtained results, specifically regarding the heterogeneity of parental time allocation to boys and children's time allocation to studying in families with less educated mothers. In addition, the result of the sensitivity analyses, where we try the estimation on different control groups (Table 9), shows a possible correlation between our exogenous variable, *Shindo*, and the time allocation to studying around the threshold 5.5, which could cause our estimates to be underestimated. One of the possible reasons for this is that there are many more children preparing for entrance examinations of (mostly) private junior high schools in Tokyo or surrounding areas (categorized into *Shindo* 5~5.5). Naturally, these children spend much more time studying than other children. We should also note that this result could be analogously discussed with the results in Table 8. Because most children preparing for entrance examinations go to cram schools, it is consistent that we do not find a significant increase in studying time when we focus on children going to cram schools (see column (4) and (5) in Table 8).

Finally, the results of our study might be less accurate than those of past studies in that our data does not include a detailed time diary. These questions and challenges are beyond the scope of our research, but further research including such data should be conducted.

Tables and Figures

Table 1

Description of *Shindo*

Shindo	Human's perception	Indoor situation	Outdoor situation
0	People do not feel any quake.	-	-
1	Felt by some people who remain quiet inside a room.	-	-
2	Felt by most people who remain quiet inside a room.	Hanging objects like lamps slightly swing.	-
3	Felt by most people inside a room.	Dishes in cupboards may rattle.	Electric wires swing slightly.
4 (3.5–4.5)	Surprised most people.	Hanging objects like ramps swing greatly. Dishes in cupboards rattle. Unstable objects may fall.	Electric wires swing greatly. Some people riding bicycles notice the quake.
5 lower (4.5–5.0)	Many people are scared by the quake.	Hanging objects like lamps swing violently. Dishes in cupboards or books in bookshelves may fall. Unstable objects fall.	People notice the telegraph poles swinging. Paved roads may be destroyed.
5 upper (5.0–5.5)	Many people find it difficult to move.	Many objects in cupboards or bookshelves fall. TVs may fall from their stand.	Windowpanes may be broken and fall. Drivers may find it difficult to drive a car.
6 lower (5.5–6.0)	People feel that it is difficult to stand.	Unstable furniture items move and may be toppled.	Tiles on the walls and windowpanes may be broken and may fall.
6 upper (6.0–6.5)	It is impossible to remain standing and move without crawling.	Most unstable furniture items move and many of them are toppled.	Tiles on the walls and windowpanes of most buildings are broken and fall. Most concrete block walls collapse if they are not reinforced.
7 (6.5-)	It is impossible to remain standing and move without crawling.	Most unstable furniture items move, are toppled, or may even be thrown into the air.	Some concrete block walls collapse even if they are reinforced.

Table 2

Results of DID for parental time allocation status

	(1)	(2)	(3)
Dependent variable	MLFP	PLFP	Afterschool
$\mathrm{I}(\mathrm{t} \geq 10) * \mathrm{Treatment}_{\mathrm{m}}$	-0.062***	0.006***	0.028*
	(0.013)	(0.002)	(0.015)
Prefecture FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
$\bar{Y}$	0.573	0.988	0.714
N	221,908	213,155	80,052
Within R^2	0.207	0.001	0.003

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 3

Results of DID for children's time allocation status

Dependent variable	(1) Study_1[a]	(2) Study_2[b]	(3) Game_1[a]	(4) Game_2[b]	(5) TV_1[a]	(6) TV_2[b]
$\mathrm{I}(t \geq 10) * \mathrm{Treatment}_m$	0.020	0.020***	0.003	0.017	-0.032**	-0.001
	(0.014)	(0.004)	(0.016)	(0.016)	(0.014)	(0.004)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.342	0.974	0.199	0.581	0.773	0.977
N	94,478	94,478	97,591	97,591	97,954	97,954
Within R^2	0.112	0.017	0.083	0.055	0.007	0.003

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 4

Results of DID for parental and children's time allocation status excluding migrated households

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
$I(t \geq 10)$	-0.063***	0.006**	0.032*	0.033**	0.020***	-0.000	0.015	-0.028**	-0.003
	(0.015)	(0.002)	(0.016)	(0.015)	(0.005)	(0.017)	(0.020)	(0.013)	(0.005)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	194,723	187,194	70,075	82,741	82,741	83,819	83,819	84,190	84,190
Within R^2	0.205	0.001	0.003	0.112	0.017	0.087	0.056	0.007	0.003

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. We excluded the households that had migrated at least once. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 5

Results of DID for parental pecuniary investment and income

	(1)	(2)	(3)
Dependent variable	LN(EXP)	LN(MINC)	LN(FINC)
$\mathrm{I}(t \geq 10) * \mathrm{Treatment}_m$	-0.068***	-0.108***	0.002
	(0.016)	(0.031)	(0.014)
Prefecture FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
$\bar{Y}$	10.345	13.994	15.389
N	205,578	80,849	130,456
Within R^2	0.185	0.142	0.044

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 6

Gender heterogeneity

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
Panel A (Boys)									
$I(t \geq 10) * Treatment_m$	-0.052***	0.007*	0.049**	0.011	0.022***	0.028	0.018	-0.025	0.004
	(0.016)	(0.004)	(0.021)	(0.017)	(0.006)	(0.023)	(0.021)	(0.017)	(0.006)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.572	0.988	0.694	0.313	0.969	0.278	0.674	0.779	0.981
N	116,324	111,882	41,944	49,499	49,499	50,169	50,169	50,368	50,368
Within R^2	0.206	0.002	0.005	0.098	0.019	0.104	0.081	0.008	0.003
Panel B (Girls)									
$I(t \geq 10) * Treatment_m$	-0.072***	0.005	0.006	0.031	0.017***	-0.027	0.007	-0.042**	-0.008
	(0.017)	(0.003)	(0.018)	(0.020)	(0.005)	(0.019)	(0.023)	(0.018)	(0.009)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.573	0.988	0.736	0.375	0.980	0.110	0.478	0.766	0.973
N	105,584	101,273	38,108	44,979	44,979	45,507	45,507	45,716	45,716
Within R^2	0.210	0.002	0.005	0.128	0.016	0.070	0.040	0.009	0.005
β_6 *in Equation (2)*									
p-value	0.426	0.738	0.092	0.394	0.512	0.068	0.863	0.467	0.326

Notes: The estimates are based on Equation (3). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. Panels A and B show the samples of boys and girls, respectively. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *: p<0.1.

Table 7

Heterogeneity based on maternal educational background

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
Panel A (Mother's education: Higher than high school)									
$\mathrm{I}(t \geq 10) * \mathrm{Treatment}_m$	-0.072***	0.010***	0.050**	-0.019	0.019***	-0.003	0.032	-0.047	-0.001
	(0.021)	(0.003)	(0.025)	(0.027)	(0.003)	(0.027)	(0.028)	(0.029)	(0.010)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.544	0.991	0.729	0.374	0.982	0.152	0.522	0.702	0.964
N	88,985	86,729	32,256	38,193	38,193	38,425	38,425	38,557	38,557
Within R^2	0.214	0.003	0.004	0.147	0.013	0.086	0.064	0.011	0.005
Panel B (Mother's education: Lower than or equal to high school)									
$\mathrm{I}(t \geq 10) * \mathrm{Treatment}_m$	-0.060***	0.005*	0.015	0.047***	0.022***	0.002	0.005	-0.022	-0.005
	(0.015)	(0.003)	(0.020)	(0.017)	(0.006)	(0.019)	(0.019)	(0.014)	(0.005)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.590	0.987	0.705	0.321	0.969	0.230	0.620	0.821	0.986
N	129,604	123,223	46,520	54,814	54,814	55,714	55,714	55,977	55,977
Within R^2	0.208	0.001	0.004	0.092	0.020	0.089	0.053	0.006	0.003
β_6 *in Equation (2)*									
p-value	0.732	0.182	0.311	0.052	0.898	0.909	0.374	0.450	0.657

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. Panels A and B show the families with mothers who have attained higher education levels (i.e., having a degree higher than that of high school) and those with mothers who have attained lower education levels (having a degree lower or equal to that of high school), respectively. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 8

Heterogeneity based on child's enrollment in cram schools (proxy of studying environment)

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
Panel A (Children not enrolled in cram schools)									
$\mathrm{I}(\mathrm{t} \geq 10) * \mathrm{Treatment}_{\mathrm{m}}$	-0.040***	0.007**	0.022	0.102***	0.042***	0.004	0.012	-0.033**	0.002
	(0.014)	(0.003)	(0.021)	(0.023)	(0.007)	(0.019)	(0.018)	(0.015)	(0.004)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.560	0.988	0.706	0.250	0.966	0.195	0.578	0.784	0.981
N	149,672	143,806	53,596	62,851	62,851	79,388	79,388	79,751	79,751
Within R^2	0.164	0.001	0.006	0.072	0.040	0.089	0.064	0.009	0.002
Panel B (Children enrolled in cram schools)									
$\mathrm{I}(\mathrm{t} \geq 10) * \mathrm{Treatment}_{\mathrm{m}}$	-0.072**	0.008	0.098	-0.096	-0.004	0.007	0.014	-0.019	-0.057**
	(0.034)	(0.007)	(0.069)	(0.067)	(0.010)	(0.052)	(0.068)	(0.058)	(0.028)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.739	0.990	0.716	0.686	0.996	0.214	0.590	0.711	0.959
N	37,019	34,961	10,878	16,080	16,080	16,288	16,288	16,333	16,333
Within R^2	0.073	0.004	0.019	0.150	0.002	0.055	0.022	0.010	0.014
β_6 *in Equation (2)*									
p-value	0.279	0.672	0.144	0.002	0.000	0.955	0.617	0.789	0.025

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. Panels A and B show the families with children not enrolled in cram schools and those with children enrolled, respectively. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 9

Different definition of control group

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
Panel A: Baseline (Replication of Table 2 and 3): Control group=Municipalities with shindo less than 5.5									
$I(t \geq 10) * Treatment_m$	-0.062***	0.006***	0.028*	0.020	0.020***	0.003	0.017	-0.032**	-0.001
	(0.013)	(0.002)	(0.015)	(0.014)	(0.004)	(0.016)	(0.016)	(0.014)	(0.004)
N	221,908	213,155	80,052	94,478	94,478	97,591	97,591	97,954	97,954
Within R^2	0.207	0.001	0.003	0.112	0.017	0.083	0.055	0.007	0.003
Panel B: Control group = Municipalities with shindo less than 5.0									
$I(t \geq 10) * Treatment_m$	-0.062***	0.005**	0.029*	0.024*	0.021***	0.002	0.012	-0.038***	-0.002
	(0.013)	(0.002)	(0.015)	(0.014)	(0.004)	(0.016)	(0.017)	(0.014)	(0.005)
N	193,487	185,774	69,774	82,394	82,394	83,370	83,370	83,745	83,745
Within R^2	0.205	0.001	0.003	0.110	0.017	0.086	0.059	0.008	0.003
Panel C: Control group = Municipalities with shindo less than 4.5									
$I(t \geq 10) * Treatment_m$	-0.056***	0.005**	0.028*	0.029**	0.021***	0.006	0.011	-0.039***	-0.001
	(0.013)	(0.002)	(0.016)	(0.014)	(0.004)	(0.016)	(0.017)	(0.014)	(0.005)
N	159,481	152,859	57,438	67,820	67,820	68,661	68,661	68,973	68,973
Within R^2	0.200	0.002	0.004	0.107	0.018	0.085	0.059	0.008	0.003

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table 10

Results without the Fukushima prefecture sample

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
Panel A: Baseline									
$I(t \geq 10) * Treatment_m$	-0.062***	0.006***	0.028*	0.020	0.020***	0.003	0.017	-0.032**	-0.001
	(0.013)	(0.002)	(0.015)	(0.014)	(0.004)	(0.016)	(0.016)	(0.014)	(0.004)
N	221,908	213,155	80,052	94,478	94,478	97,591	97,591	97,954	97,954
Within R^2	0.207	0.001	0.003	0.112	0.017	0.083	0.055	0.007	0.003
Panel B: Excluding households in Fukushima prefecture									
$I(t \geq 10) * Treatment_m$	-0.053***	0.004	0.022	0.010	0.020***	-0.001	0.023	-0.027*	-0.002
	(0.015)	(0.002)	(0.017)	(0.014)	(0.005)	(0.018)	(0.018)	(0.015)	(0.005)
N	218,350	209,763	78,739	92,948	92,948	94,083	94,083	94,486	94,486
Within R^2	0.208	0.001	0.003	0.111	0.017	0.086	0.057	0.007	0.003

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. (a): The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: $p < 0.01$, **: $p<0.05$, *<0.1

Figure 1

Location of seismological stations

Notes: The dots on the map indicate the location of seismological stations. All the seismological stations are administered by JMA.

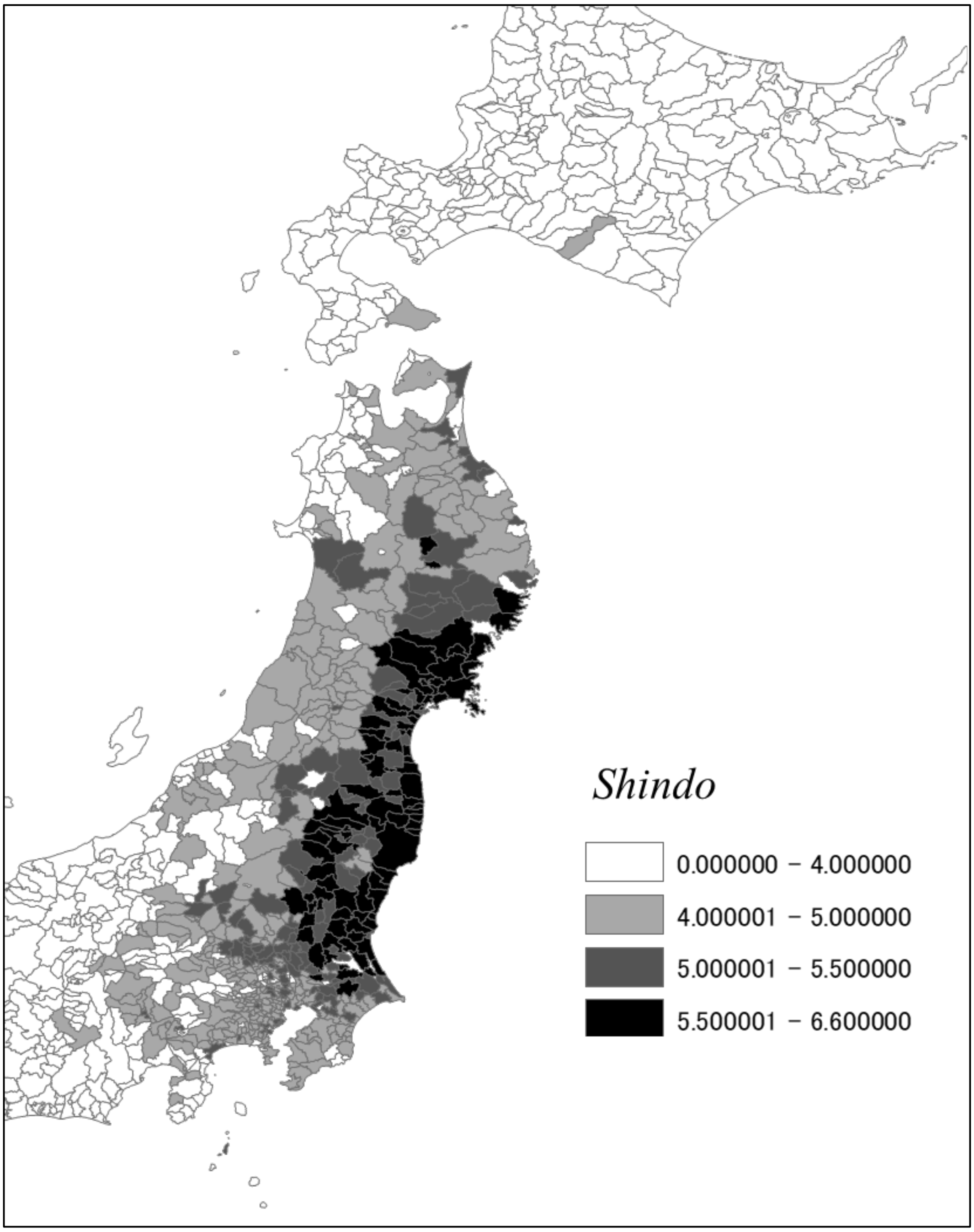


Figure 2

Seismic intensity (*Shindo*)

Notes: The treatment variable of our study is based on seismic intensity (*Shindo* in Japanese), which is defined by JMA and measured in each seismological station. We focused only on the main quake of the Earthquake for the simplicity of defining the treatment intensity. From the data collected by each seismological station, we constructed a municipality-level intensity based on the procedure explained in the manuscript.

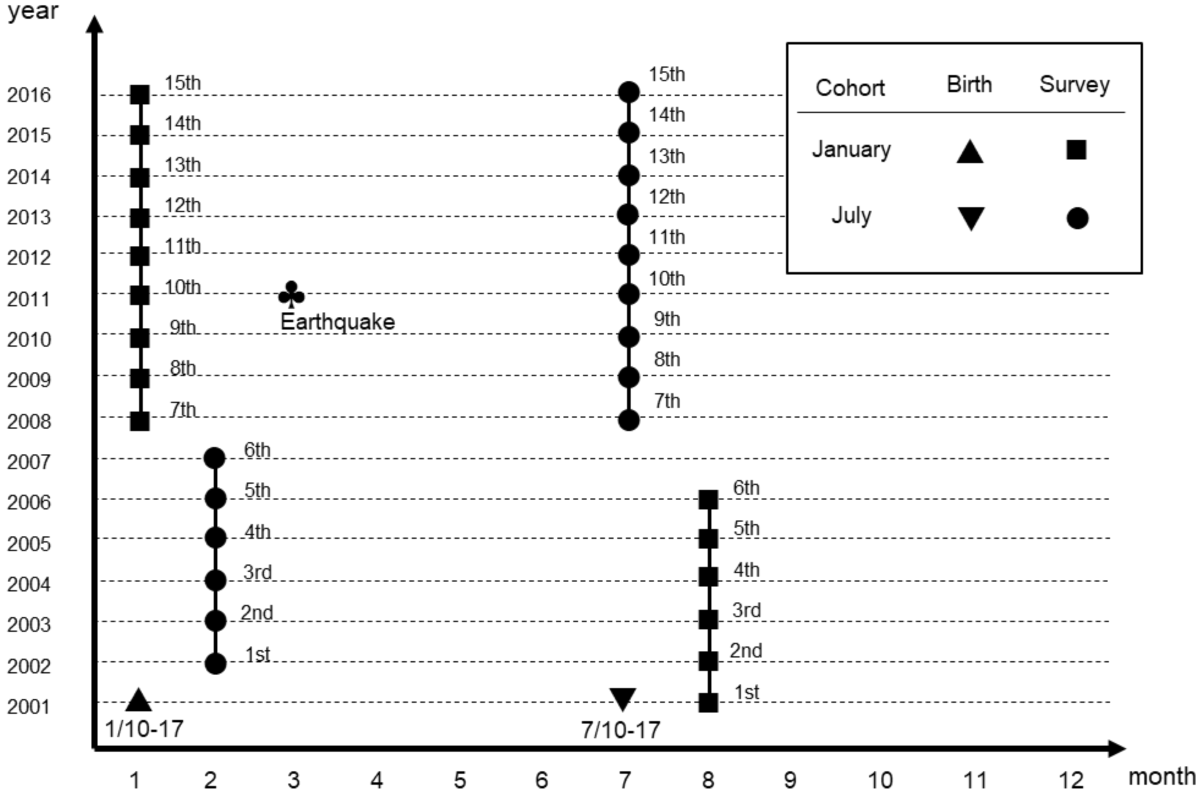


Figure 3

Basic structure of LSN21

Notes: Children in each cohort were surveyed after about 6 months of their birthday every year until the sixth survey. From the seventh to the latest surveys, the follow-up questionnaires were sent around their birthday every year. The Earthquake occurred in March 2011, which is depicted by a clover mark in the above figure.

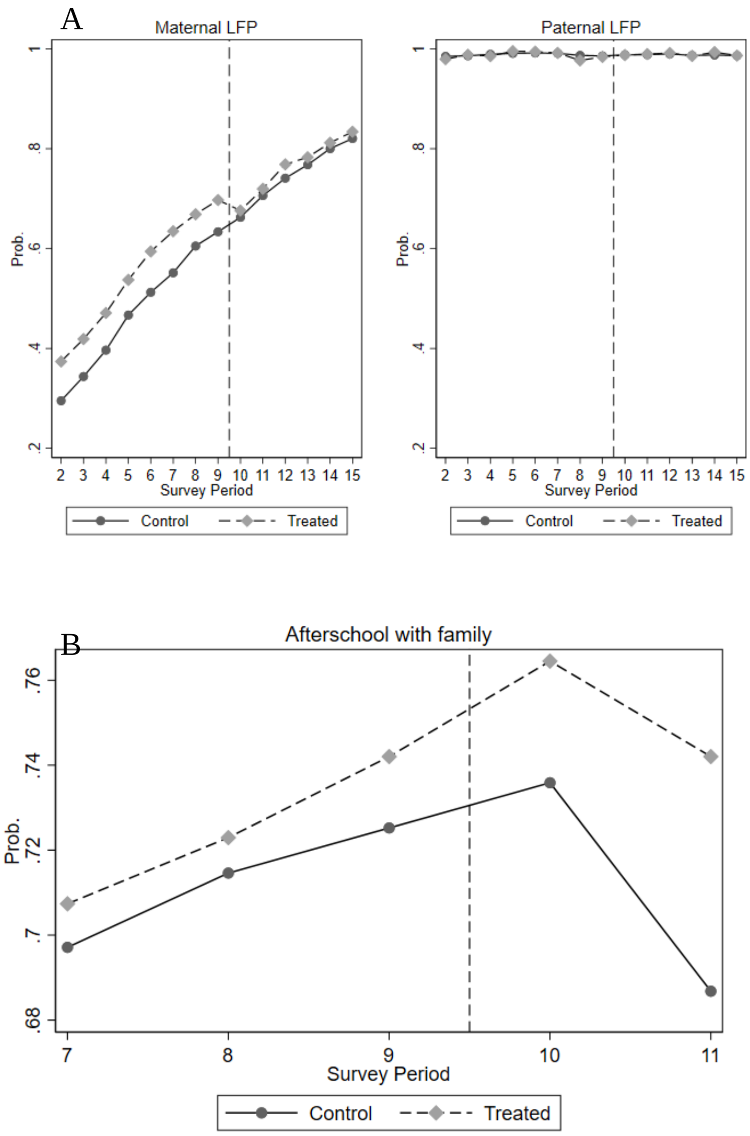


Figure 4

Descriptive statistics of (A) parental labor force participation (LFP) and (B) the probability that children spend time with family members after school.

Notes: Data are drawn from the Longitudinal Survey of Newborns in the 21st Century, waves 2–15 for Panel A and 7–11 for Panel B.

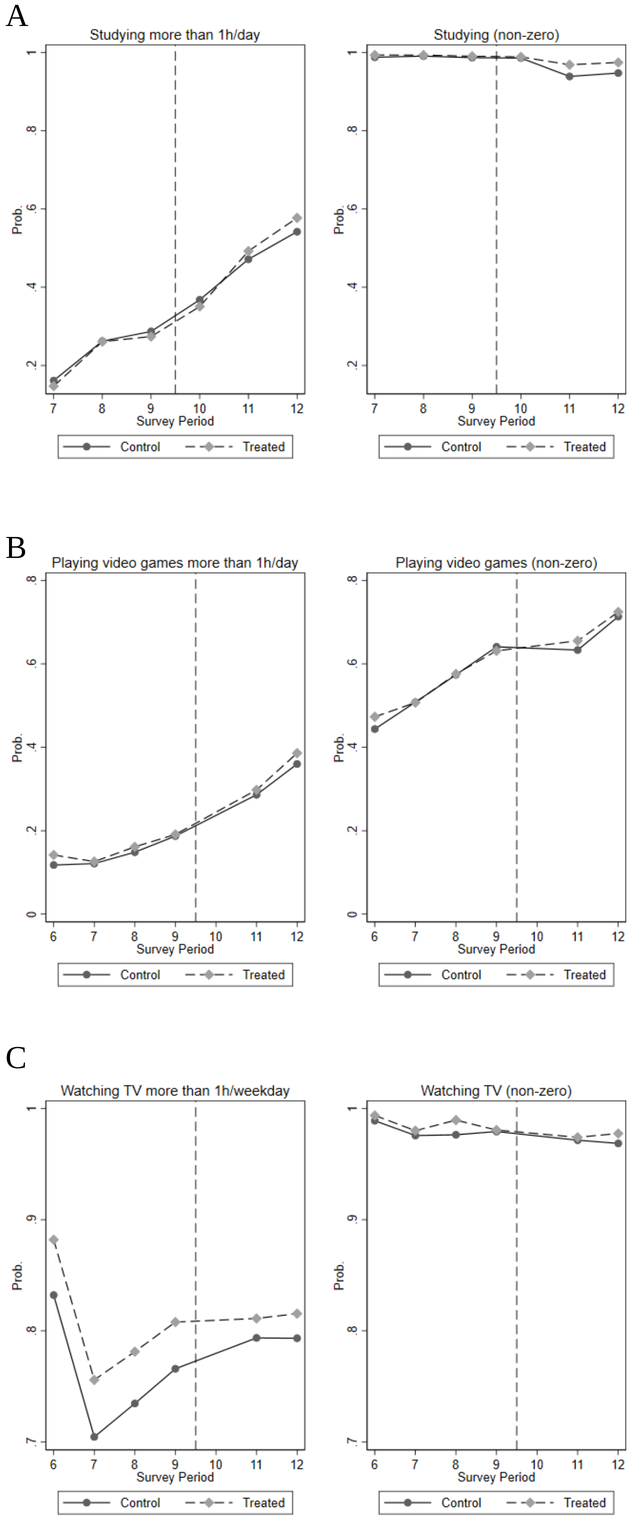


Figure 5

Descriptive statistics of children's own time investment for (A) studying, (B) playing video games, and (C) watching TV.

Notes: Data are drawn from the Longitudinal Survey of Newborns in the 21st Century, waves 7–12 for Panel A and 6–12 (excluding the 10th survey due to the reason stated in footnote ##) for Panels B and C.

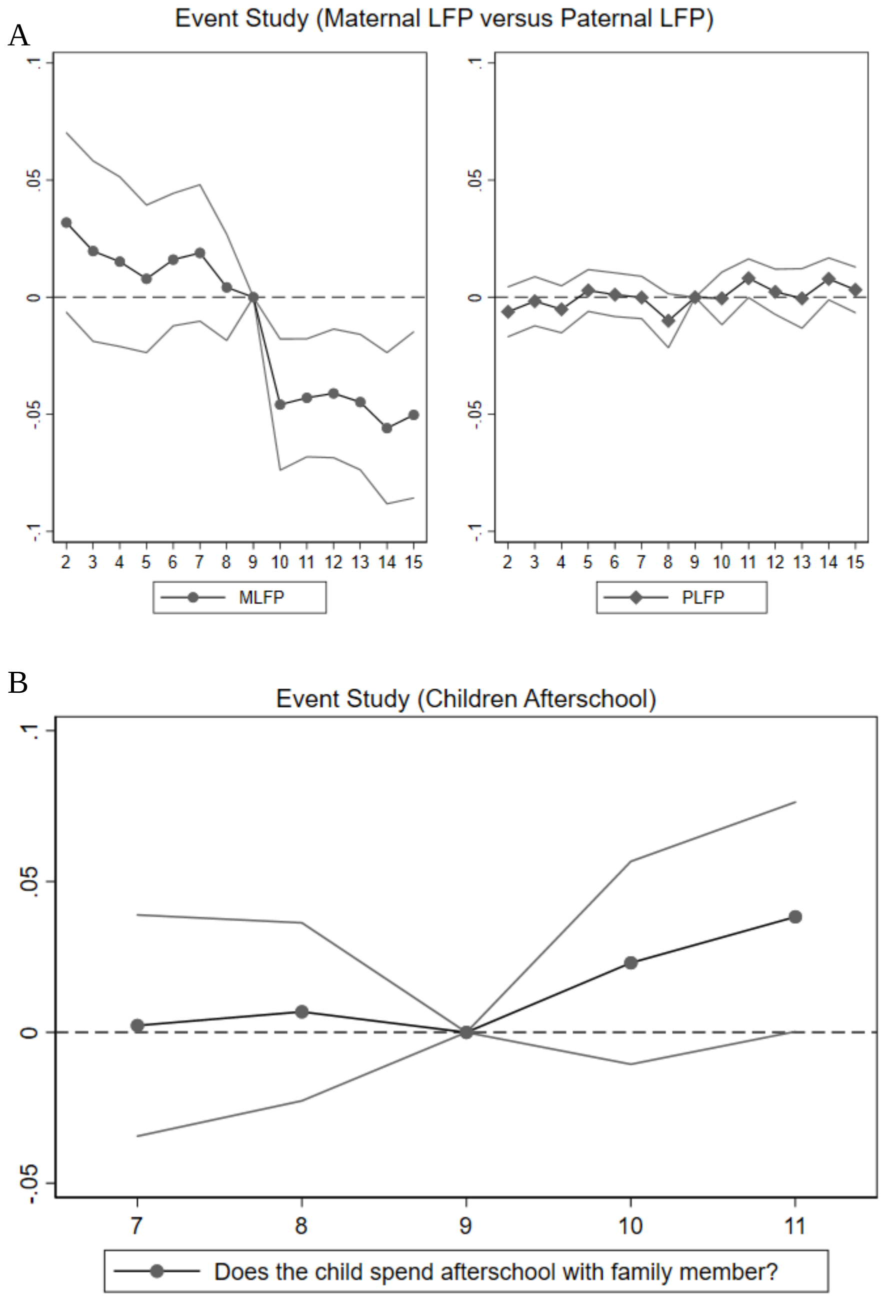


Figure 6

Results of the event study (parental time allocation)

Notes: This figure is based on the results of the event study associated with Equation (1). The outcome variables are of parental time allocation status; that is, labor force participation and whether the children spend time with family members after school. The lines are the 90% confidence intervals, where standard errors are clustered by the municipality level. The reference period is the 9th survey, one year before the Earthquake.

A B

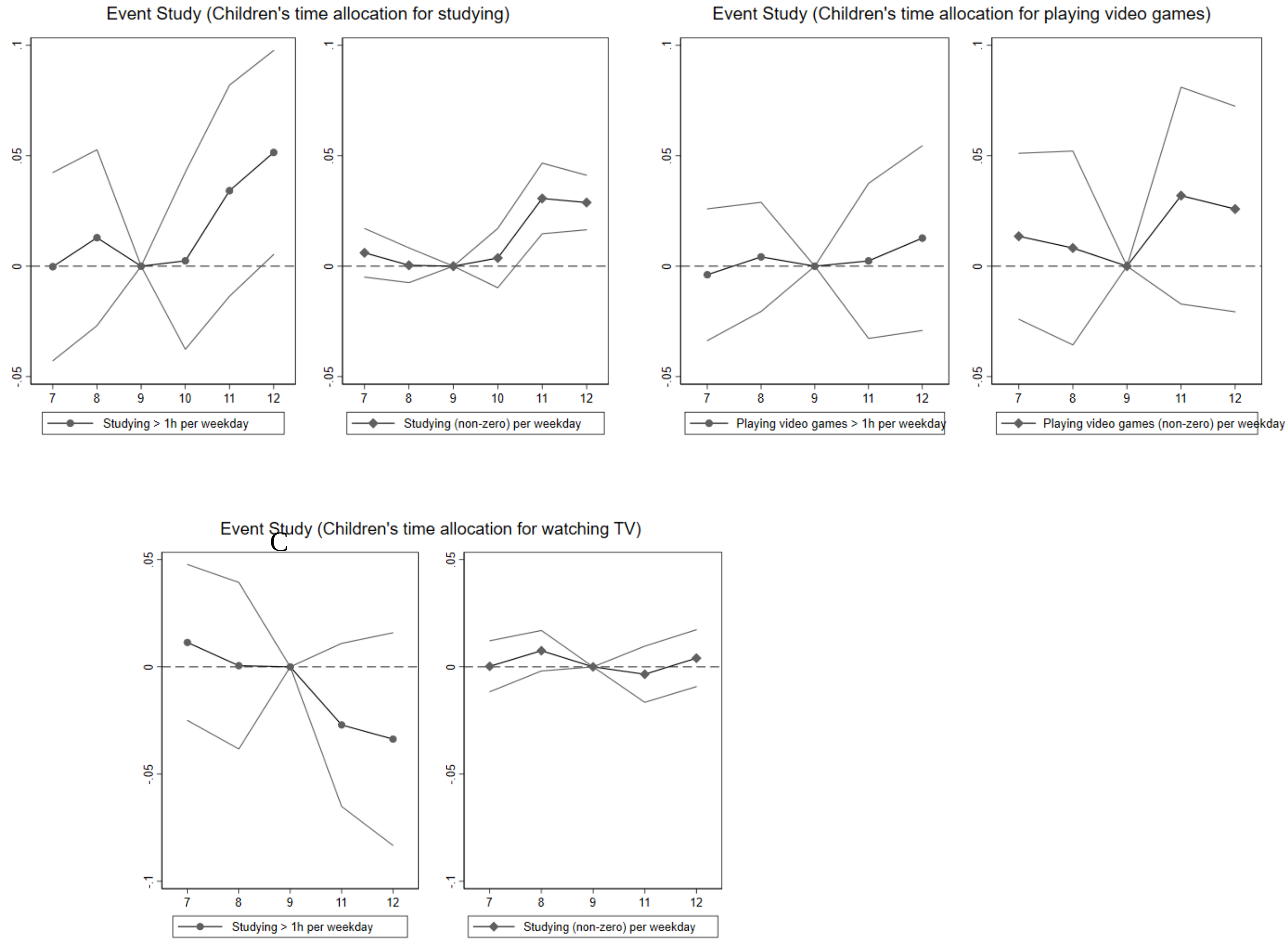


Figure 7

Results of the event study (children's time allocation)

Notes: This figure is based on the results of the event study associated with Equation (1). The outcome variables are of children's own time allocation status; that is, time spent studying, playing video games, and watching TV. The lines are the 90% confidence intervals, where standard errors are clustered by the municipality level. The reference period is the 9th survey, one year before the Earthquake.

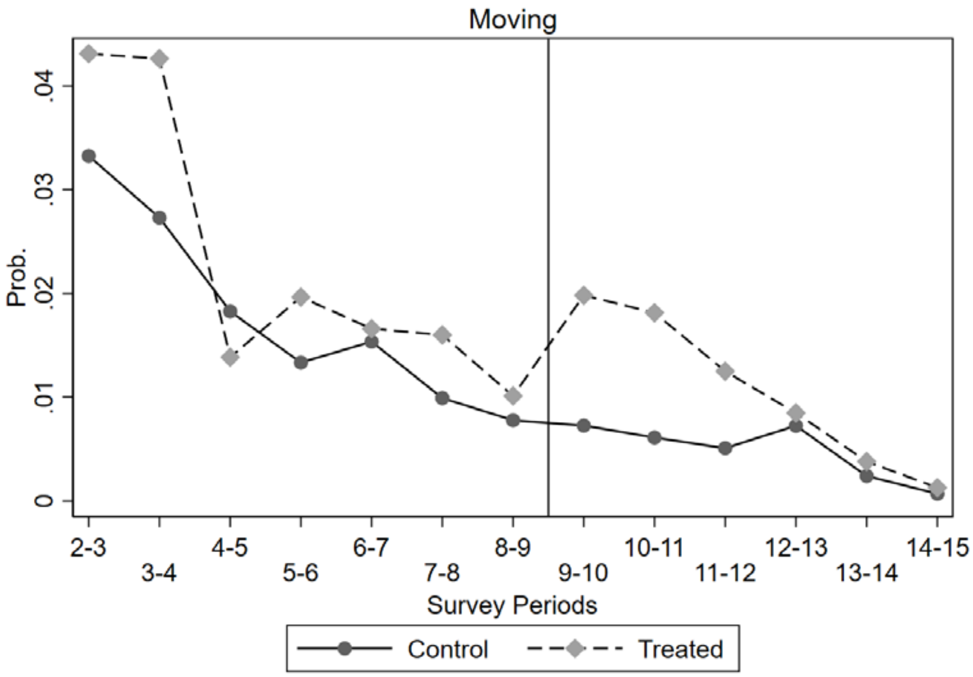


Figure 8
The probability of migration

Table A1

Inclusion of the *January Cohort*

	Parental outcomes			Children's outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	MLFP	PLFP	Afterschool	Study_1[a]	Study_2[b]	Game_1[a]	Game_2[b]	TV_1[a]	TV_2[b]
$\mathrm{After}_t * \mathrm{Treatment}_m$	-0.047***	0.003	0.037***	0.034***	0.017***	0.011	0.020*	-0.018**	0.002
	(0.011)	(0.002)	(0.011)	(0.012)	(0.004)	(0.011)	(0.011)	(0.009)	(0.003)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{Y}$	0.572	0.988	0.734	0.349	0.974	0.212	0.601	0.780	0.979
N	439,562	422,810	159,714	188,619	188,619	193,183	193,183	193,853	193,853
Within R^2	0.202	0.001	0.004	0.103	0.021	0.081	0.069	0.007	0.002

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We defined the treatment group as municipalities with *Shindo* 6–7. Standard errors are clustered by the municipality level, which is reported in parentheses. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Table A2

Inclusion of the 10th survey (the results of children's time allocation for playing video games and watching TV and the expenditure for children are reported)

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Game_1	Game_2	TV_1	TV_2	LN(EXP)
$\text{After}_t * \text{Treatment}_m$	0.003	0.017	-0.032**	-0.001	-0.068***
	(0.016)	(0.016)	(0.014)	(0.004)	(0.016)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
N	97,591	97,591	97,954	97,954	205,578
Within R^2	0.083	0.055	0.007	0.003	0.185

Notes: The estimates are based on Equation (1). We used the data from LSN21 and the seismic information measured by Japanese Meteorological Association. We included the data from the 10th survey (please see the increase in sample size compared to Table 3 and 5). Standard errors are clustered by the municipality level, which is reported in parentheses. (a) The outcome variable takes 1 if the children spend more than 1 hour per day (/weekday) for this activity, and (b) the outcome variable takes 1 if the children spend non-zero minutes per day (/weekday) for this activity. Inference ***: p < 0.01, **: p<0.05, *<0.1

Figure A1

Test of the common trend assumption for heterogeneity analysis 1 (boy's subsample)

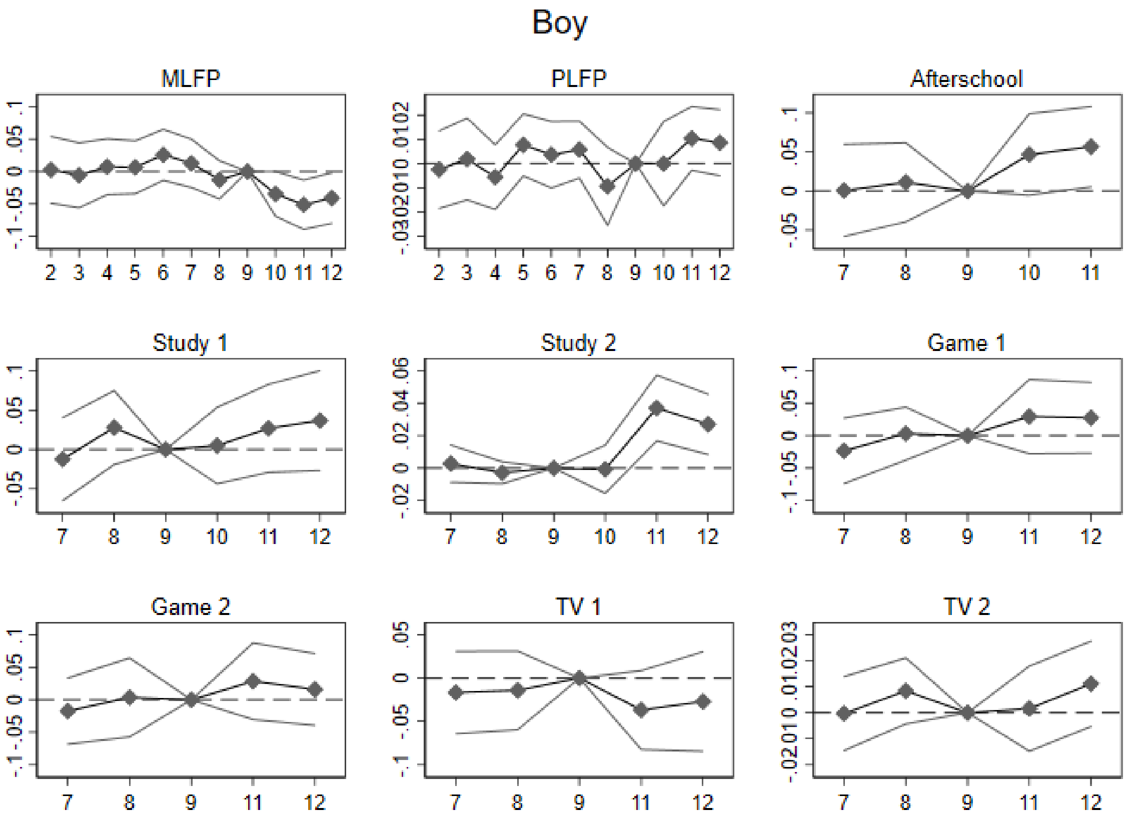


Figure A2

Test of the common trend assumption for heterogeneity analysis 2 (girl's subsample)

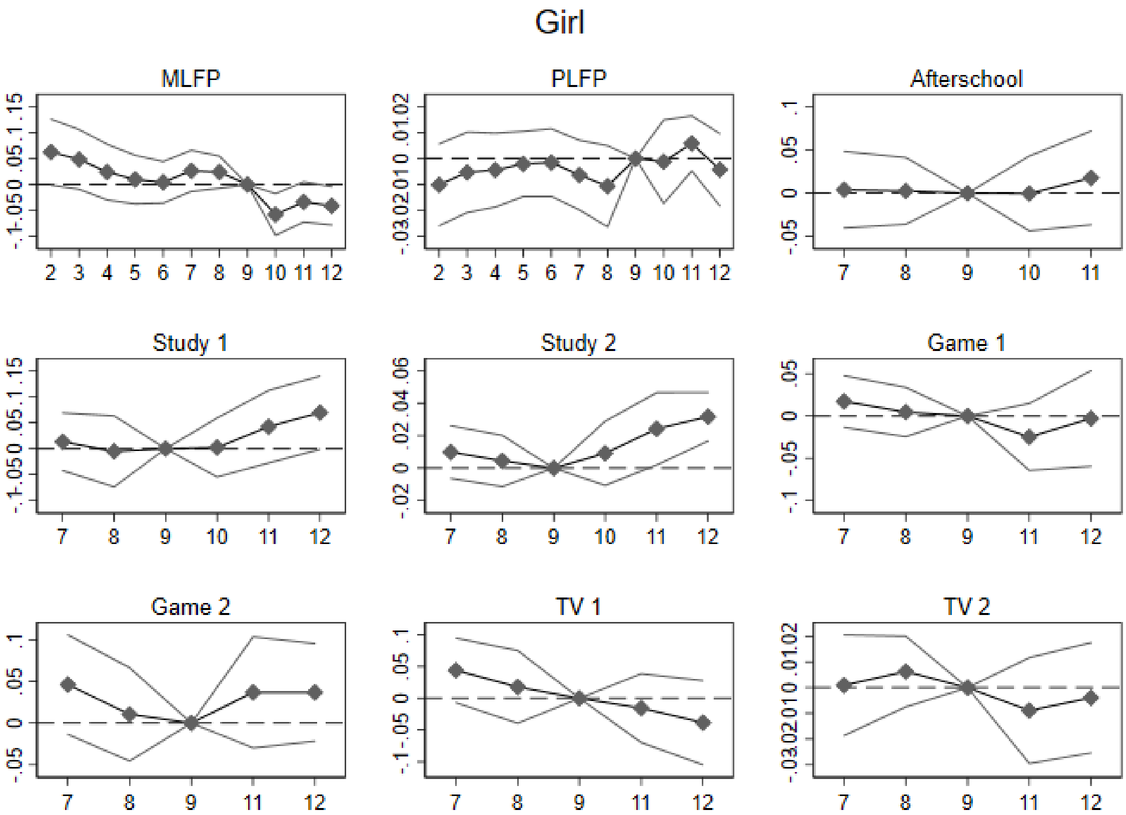


Figure A3

Test of the common trend assumption for heterogeneity analysis 3 (mother's higher education subsample)

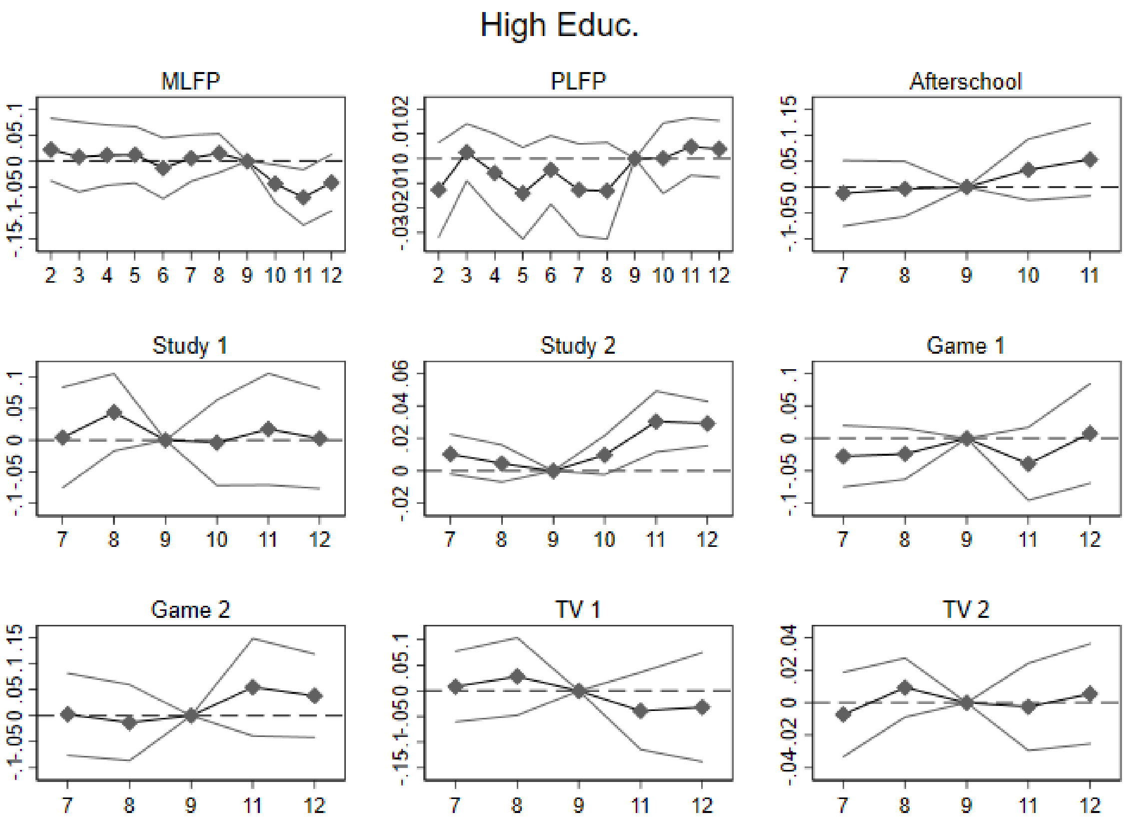


Figure A4

Test of the common trend assumption for heterogeneity analysis 4 (mother's lower education subsample)

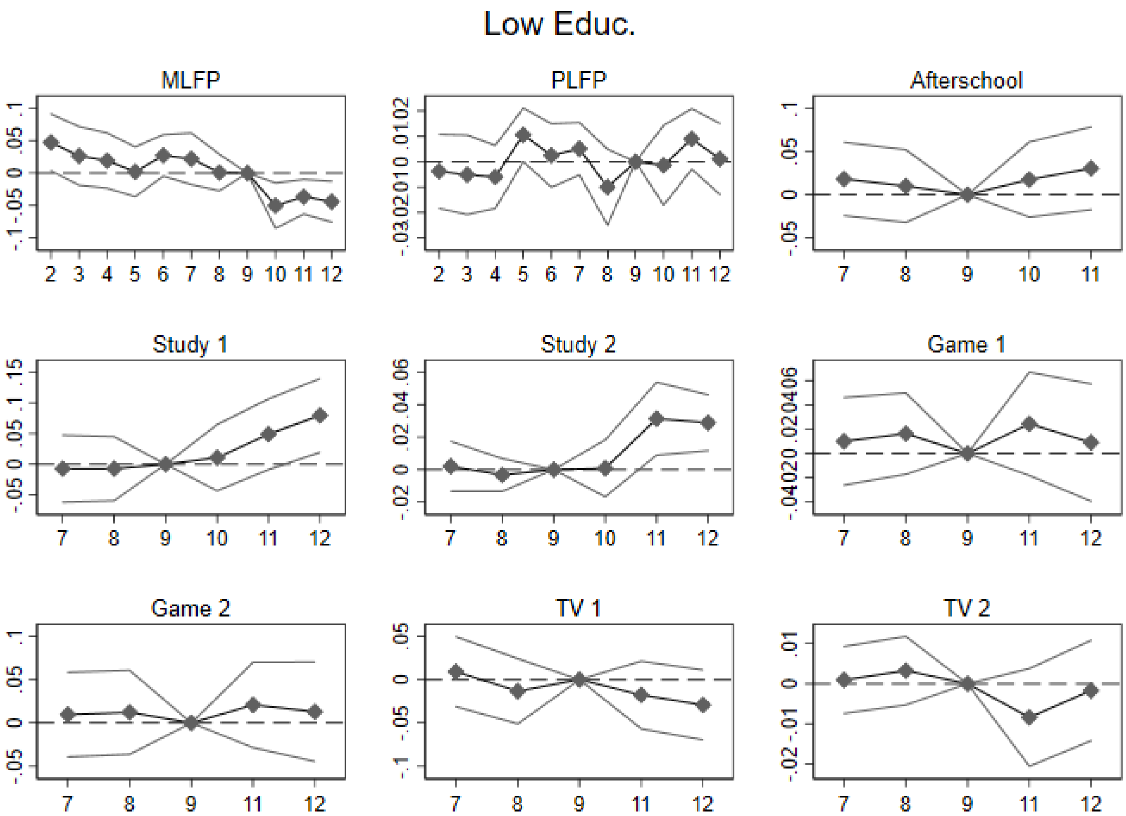


Figure A5

Test of the common trend assumption for heterogeneity analysis 5 (“no cram school” subsample)

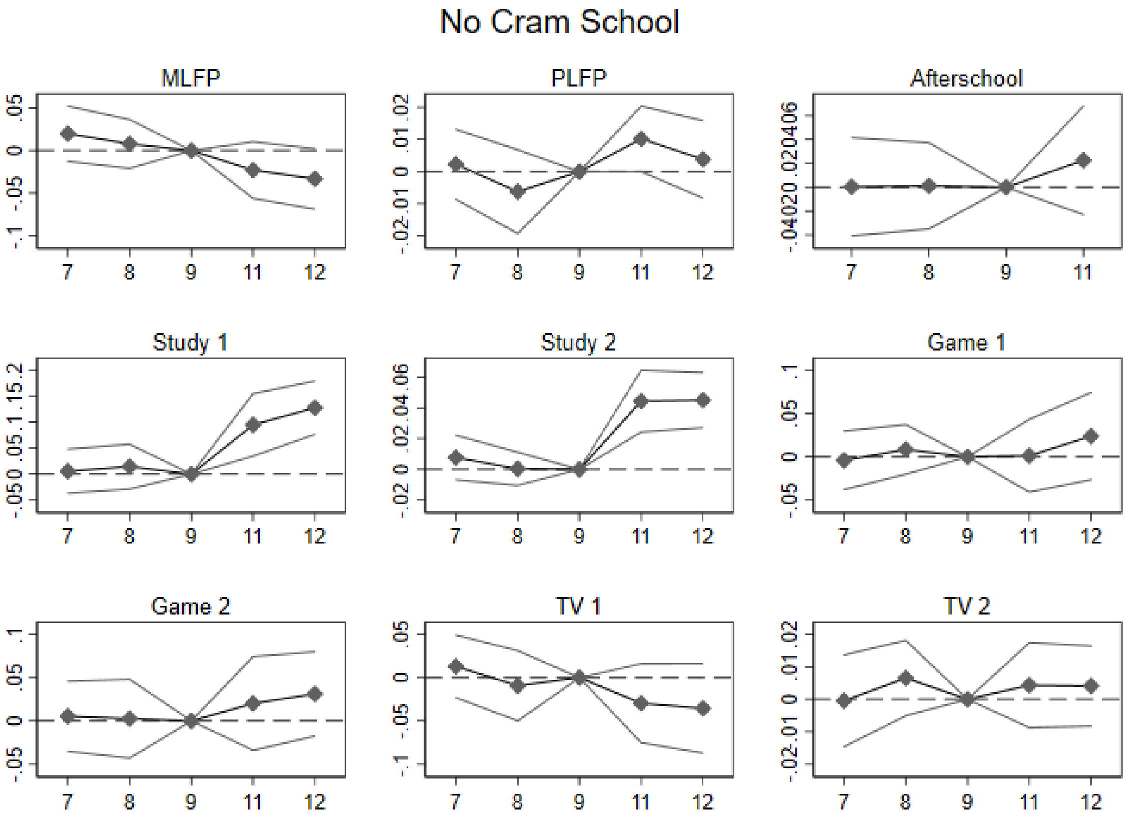


Figure A6

Test of the common trend assumption for heterogeneity analysis 5 (cram school subsample)

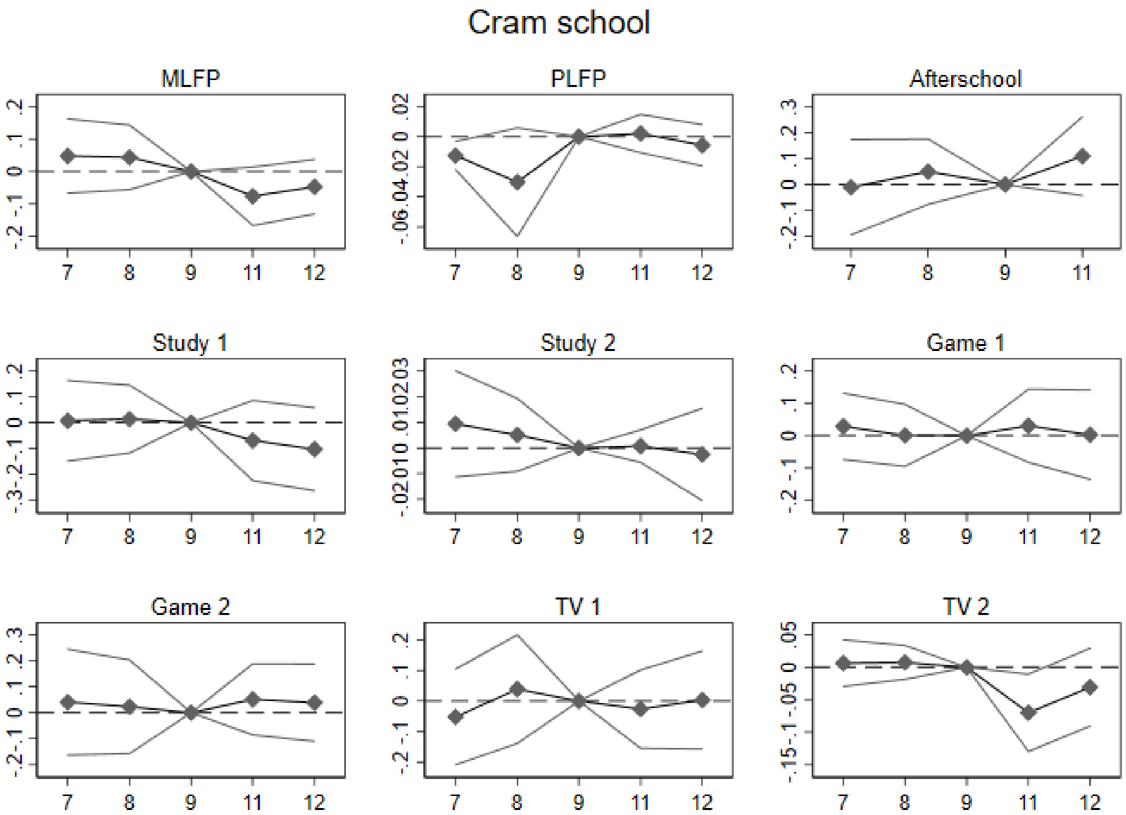


Figure A7

Test of the common trend assumption for different control group 1 (control group: *Shindo* < 5.0)

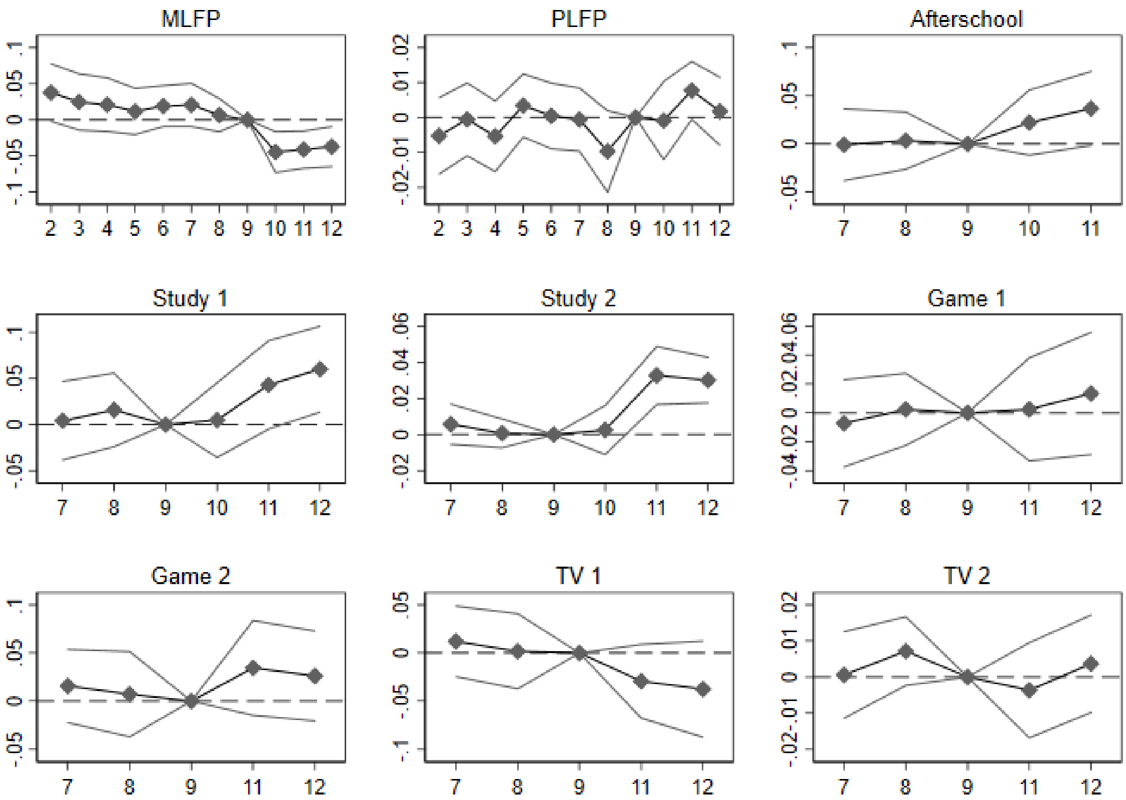
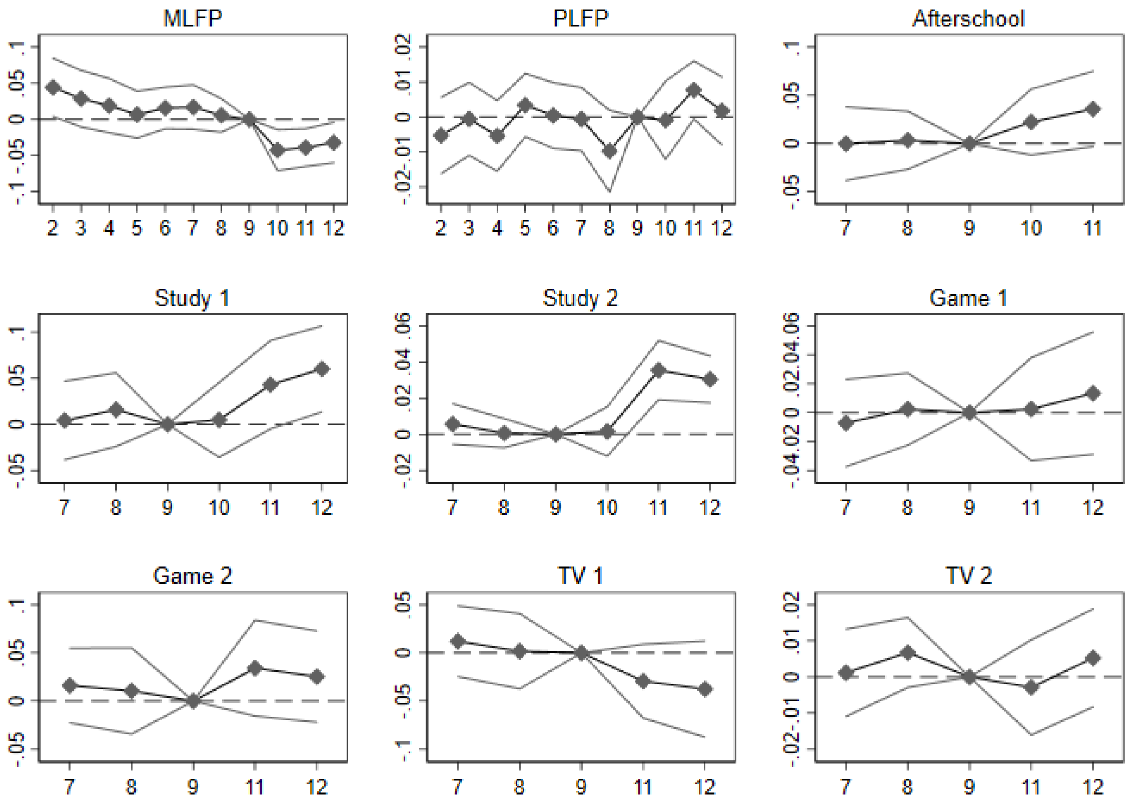


Figure A8

Test of the common trend assumption for different control group 2 (control group: *Shindo* < 4.5)



References

Aldrich, Daniel P., and Yasuyuki Sawada. 2015. "The Physical and Social Determinants of Mortality in the 3.11 Tsunami." *Social Science & Medicine* 124:66–75. https://doi.org/10.1016/j.socscimed.2014.11.025

Almond, Douglas, and Janet Currie. 2011. "Human Capital Development before Age Five." *Handbook of Labor Economics* Vol. 4.B: 1315–1486. Elsevier. https://doi.org/10.1016/S0169-7218(11)02413-0.

Angrist, Joahua and Jorn-steffen Pischke. 2008. "Mostly Harmless Econometrics: An Empiricist's Companion" 227–242 (Chapter 5.2). NJ, United States: Princeton University Press.

Attanasio, Orazio, Costas Meghir, and Emily Nix. 2015. "Human Capital Development and Parental Investment in India." National Bureau of Economic Research (NBER) Working Paper 21740. http://www.nber.org/papers/w21740.

Autor, David. 2003. "Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing". *Journal of Labor Economics* 21(1):1–42. https://doi.org/10.1086/344122

Becker, Gary. 1962. "Investment in Human Capital: A Theoretical Analysis". *Journal of Political Economy* 70(5):9–49. https://doi.org/10.1086/258724

Baker, Michael, Jonathan Gruber, and Kevin Milligan. 2008. "Universal Child Care, Matemal Labor Supply, and Family Well-Being." *Journal of Political Economy* 116(4):709–45. https://doi.org/10.1086/591908.

Borga, Liyousew Gebremedhin. 2019. "Children's Own Time Use and Its Effect on Skill Formation." *Journal of Development Studies* 55(5):876–93. https://doi.org/10.1080/00220388.2018.1499893.

Caetano, Carolina. 2015. "A Test of Exogeneity without Instrumental Variables in Models with Bunching." *Econometrica* 83(4):1581–1600. https://doi.org/10.3982/ecta11231.

Caetano, Gregorio, Josh Kinsler, and Hao Teng. 2019. "Towards Causal Estimates of Children's Time Allocation on Skill Development." *Journal of Applied Econometrics* 34(4):588–605. https://doi.org/10.1002/jae.2700.

Cameron, Lisa, and Manisha Shah. 2015. "Risk-Taking Behavior in the Wake of Natural Disasters." *Journal of Human Resources* 50(2):484–515. https://doi.org/10.3368/jhr.50.2.484.

Carneiro, Pedro, Costas Meghir, and Matthias Parey. 2013. "Maternal Education, Home Environments, and the Development of Children and Adolescents." *Journal of the European Economic Association* 11 (SUPPL. 1):123–60. https://doi.org/10.1111/j.1542-4774.2012.01096.x.

Carneiro, Pedro, and Margarida Rodrigues. 2009. "Evaluating the Effect of Maternal Time on Child Development Using the Generalized Propensity Score." unpublished. http://www.iza.org/conference_files/SSch2009/rodrigues_m5050.pdf.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. 2013. "Catastrophic Natural Disasters and Economic Growth." *Review of Economics and Statistics* 95(5):1549–61. https://doi.org/10.1162/REST_a_00413.

Chen, Yuyu, and Li An Zhou. 2007. "The Long-Term Health and Economic Consequences of the 1959-1961 Famine in China." *Journal of Health Economics* 26(4):659–81. https://doi.org/10.1016/j.jhealeco.2006.12.006.

Coffman, Makena, and Ilan Noy. 2012. "Hurricane Iniki: Measuring the Long-Term Economic Impact of a Natural Disaster Using Synthetic Control." *Environment and Development Economics* 17(2):187–205. https://doi.org/10.1017/S1355770X11000350.

Cunha, Flavio, and James Heckman. 2007. "The Technology of Skill Formation." *American Economic Review* 97(2):31–47. https://doi.org/10.1257/aer.97.2.31.

Cunha, Flavio, and James J. Heckman. 2008. "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Journal of Human Resources* 43(4):738–82. https://doi.org/10.3368/jhr.43.4.738.

Currie, Janet, and Mark Stabile. 2003. "Socioeconomic Status and Child Health: Why Is the Relationship Stronger for Older Children?" *American Economic Review* 93(5):1813–23. https://doi.org/10.1257/000282803322655563.

Currie, Janet, and Maya Rossin-Slater. 2013. "Weathering the Storm: Hurricanes and Birth Outcomes." *Journal of Health Economics* 32(3):487–503. https://doi.org/10.1016/j.jhealeco.2013.01.004.

Currie, Janet. 2009. “Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development.” *Journal of Economic Literature* 47(1): 87–122. https://doi.org/10.1257/jel.47.1.87.

Dearden, Lorraine, Stephen Machin, and Howard Reed. 1997. “Intergenerational Mobility in Britain.” *Economic Journal* 107(440):47–66. https://doi.org/10.1111/1468-0297.00141

Del Boca, Daniela, Chiara Monfardini, and Cheti Nicoletti. 2017. “Parental and Child Time Investments and the Cognitive Development of Adolescents.” *Journal of Labor Economics* 35(2):565–608. https://doi.org/10.1086/689479.

Del Boca, Daniela, Christopher Flinn, and Matthew Wiswall. 2014. “Household Choices and Child Development.” *Review of Economic Studies* 81(1):137–85. https://doi.org/10.1093/restud/rdt026.

Del Bono, Emilia, Marco Francesconi, Yvonne Kelly, and Amanda Sacker. 2016. “Early Maternal Time Investment and Early Child Outcomes.” *Economic Journal* 126(596):F96–135. https://doi.org/10.1111/ecoj.12342.

Deuchert, Eva, and Christina Felfe. 2015. “The Tempest: Short- and Long-Term Consequences of a Natural Disaster for Children’s Development.” *European Economic Review* 80 (March 2013):280–94. https://doi.org/10.1016/j.euroecorev.2015.09.004.

Fiorini, Mario, and Michael P. Keane. 2014. “How the Allocation of Children’s Time Affects Cognitive and Noncognitive Development.” *Journal of Labor Economics* 32(4):787–836. https://doi.org/10.1086/677232.

Fiorini, Mario. 2010. “The Effect of Home Computer Use on Children’s Cognitive and Non-Cognitive Skills.” *Economics of Education Review* 29(1):55–72. https://doi.org/10.1016/j.econedurev.2009.06.006.

Fort, Margherita, Andrea Ichino, and Giulio Zanella. 2020. “Cognitive and Noncognitive Costs of Day Care at Age 0–2 for Children in Advantaged Families.” *Journal of Political Economy* 128(1):158–205. https://doi.org/10.1086/704075.

Francesconi, Marco, and James J. Heckman. 2016. “Child Development and Parental Investment: Introduction.” *Economic Journal* 126(596):F1–27. https://doi.org/10.1111/ecoj.12388.

Groppo, Valeria, and Kati Kraehnert. 2017. “The Impact of Extreme Weather Events on Education.” *Journal of Population Economics* 30. https://doi.org/10.1007/s00148-016-0628-6.

Gupta, Nabanita Datta, and Marianne Simonsen. 2010. “Non-Cognitive Child Outcomes and Universal High Quality Child Care.” *Journal of Public Economics* 94(1–2):30–43. https://doi.org/10.1016/j.jpubeco.2009.10.001.

Halla, Martin, and Martina Zweimuller. 2014. “Parental Response to Early Human Capital Shocks: Evidence from the Chernobyl Accident.” IZA Discussion Paper No. 7968. http://repec.iza.org/dp7968.pdf.

Hanaoka, Chie, Hitoshi Shigeoka, and Yasutora Watanabe. 2018. “Do Risk Preferences Change? Evidence from the Great East Japan Earthquake.” *American Economic Journal: Applied Economics* 10(2):298–330. https://doi.org/10.1257/app.20170048.

Haworth, A., 2013. “After Fukushima: families on the edge of meltdown.” The Guardian. [online]. https://www.theguardian.com/environment/2013/feb/24/divorce-after-fukushima-nuclear-disaster. (Accessed on March 10, 2020)

Heckman, James J. 2006. “Investing in Disadvantaged Children.” *Science* 312(5782):1900–1902. https://doi.org/10.1016/j.adolescence.2005.09.001.

Li, Yiyuan, Hong Li, Jean Decety, and Kang Lee. 2013. “Experiencing a Natural Disaster Alters Children’s Altruistic Giving.” *Psychological Science* 24(9):1686–95. https://doi.org/10.1177/0956797613479975.

Loayza, Norman V., Eduardo Olaberría, Jamele Rigolini, and Luc Christiaensen. 2012. “Natural Disasters and Growth: Going Beyond the Averages.” *World Development* 40(7):1317–36. https://doi.org/10.1016/j.worlddev.2012.03.002.

Managi, Shunsuke, and Dabo Guan. 2017. “Multiple Disasters Management: Lessons from the Fukushima Triple Events.” *Economic Analysis and Policy* 53:114–22. https://doi.org/10.1016/j.eap.2016.12.002.

National Police Agency. 2019. “The Damage of Great East Japan Earthquake” https://www.npa.go.jp/news/other/earthquake2011/pdf/higaijokyo.pdf (Accessed in August 20, 2019) (in Japanese).

Nguyen, Ha Trong, Huong Thu Le, and Luke B. Connelly. 2019. “Weather and Children’s Time Allocation,” Life Course Centre Working Paper Series, 2019-13. Institute for Social Science Research, The University of Queensland. https://www.researchgate.net/profile/Ha_Nguyen240/publication/333894071_Weather_and_Children's_Time_Allocation/links/5d0b4a84299bf1f539d18e5d/Weather-and-Childrens-Time-Allocation.pdf

Nikkei. 2011. “Almost All the Dead of the Great East Japan Earthquake Are Caused by Tsunami” https://www.nikkei.com/article/DGXNASDG1902Z_Z10C11A4CC1000/ (Accessed on March 10, 2020)

Okada, Norio, Tao Ye, Yoshio Kajitani, Peijun Shi, and Hirokazu Tatano. 2011. “The 2011 Eastern Japan Great Earthquake Disaster: Overview and Comments.” *International Journal of Disaster Risk Science* 2(1):34–42. https://doi.org/10.1007/s13753-011-0004-9.

Rehdanz, Katrin, Heinz Welsch, Daiju Narita, and Toshihiro Okubo. 2015. “Well-Being Effects of a Major Natural Disaster: The Case of Fukushima.” *Journal of Economic Behavior and Organization* 116:500–517. https://doi.org/10.1016/j.jebo.2015.05.014.

Sata, Fumihiro, Hideoki Fukuoka, Takeshi Ozaki, Yoshiya Ito, Nobuo Yoshiike, and Hidemi Takimoto. 2017. “21-Seiki Shusshouji Jyudan Chosa no Gaiyo: Ko no Hatsuiku ni Eikyo wo Oyobosu Yoin.” (The Summary of Longitudinal Survey of Newborns in the 21st Century: The Factors Which Affect Children’s Growth). *Japan Hygieiology Journal* 72(1):15-19. (in Japanese) https://doi.org/10.1265/jjh.72.15.

Skidmore, Mark, and Hideki Toya. 2002. “Do Natural Disasters Promote Long-Run Growth?” *Economic Inquiry* 40(4):664–87. https://doi.org/10.1093/ei/40.4.664.

Sugano, Saki. 2016. “The Well-Being of Elderly Survivors after Natural Disasters: Measuring the Impact of the Great East Japan Earthquake.” *Japanese Economic Review* 67(2):211–29. https://doi.org/10.1111/jere.12103.

Todd, Petra, and Kenneth I. Wolpin. 2007. “The Production of Cognitive Achievement in Children: Home, School and Racial Test Score Gaps.” *Journal of Human Capital* 1(1):91-136. https://www.jstor.org/stable/10.1086/526401.

Vivoda, Vlado. 2012. “Japan’s Energy Security Predicament Post-Fukushima.” *Energy Policy* 46:135–43. https://doi.org/10.1016/j.enpol.2012.03.044.

Yamaguchi, Shintaro, Yukiko Asai, and Ryo Kambayashi. 2018. “Effects of Subsidized Childcare on Mothers’ Labor Supply under a Rationing Mechanism.” *Labour Economics* 55 (August):1–17. https://doi.org/10.1016/j.labeco.2018.09.002.