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How Does Flood Affect Children Differently? The Impact of Flood on Children's Education, Labor, Food Consumption, and Cognitive Development

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Abstract

This paper contributes an in-depth study of the short- and long-term effects of floods on the cognitive development of school-aged children. Specifically, we exploit individual-level microdata from a longitudinal study of childhood poverty in Vietnam. Our analyses indicate that floods immediately imposed negative impacts on children's cognitive skills, but these impacts would be mitigated in the long run. Changes in child schooling, time allocation between school and work, and household food consumption (child nutrition) appear to be potential channels behind these impacts. Girls, older children, firstborn children, and children belonging to ethnic minorities are more vulnerable to the adverse effects of flooding. Our results suggest that policies to alleviate the credit constraints of households in the above groups could mitigate the damage imposed by natural disasters on human capital accumulation.

Keywords: Cognitive skills, Natural disasters, Child labor, Education, Ethnic minority

JEL Codes: I24 I26 J13 J15 J16 J22 J24 Q54

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1. Introduction

Natural disasters and their adverse impacts in Vietnam and many Southeast Asian countries are expected to be exacerbated by climate change. Its geographic location constantly exposes Vietnam to disasters such as floods, storms, landslides, and droughts. In 2018, Vietnam ranked sixth among those countries most affected by climate-related disasters (Eckstein et al., 2019). Natural disasters were responsible for 9,500 deaths and a 1.5 percent loss in annual GDP during the 2001–2010 period (USAID, 2017).

By 2050, the annual rainfall in Vietnam is projected to increase by 2–7 percent, with more extreme variation occurring between the dry and rainy seasons. As a result, natural disasters are becoming more frequent and intense due to climate change. Historical data from 1953 to 2021 shows a dramatic increase in the national occurrences of climate-related disasters over time (see Figure 1). The agricultural sector is predicted to be the worst affected, which may threaten the livelihoods of rural households, which account for over 70 percent of the total population. Furthermore, extreme weather events such as heatwaves, floods, and drought can exert long-lasting adverse effects on employment outcomes by interrupting schooling and inhibiting the cognitive skill development of children.

In the last few decades, the combined effects of natural disasters and climate change have seriously threatened the lives and well-being of children and their families. Large flood events, such as the 2020 floods in central Vietnam, still cause significant disruption and represent a serious hazard to children. The short-term impacts of floods on children include injuries and displacements, while the longer-term impacts include waterborne diseases, malnutrition due to crop damage, and disruption in education. With the increasing frequency of these events resulting from climate change, there is a growing concern that vulnerable children will be increasingly negatively affected over the following decades.

[Insert Figure 1 here]

The idea that natural disasters experienced during childhood can disrupt human capital accumulation is well established in the literature. The impacts of such events have been found to significantly reduce school attainment (Björkman-Nyqvist, 2013; Gitter and Barham, 2007;

Hyland and Rush, 2019; Paudel and Ryu, 2018), increase child labor (Alvi and Dendir, 2011; Dumas, 2020; Nordma et al., 2022; Takasaki, 2017), adversely affect employment (Adhvaryu et al., 2018; Carrillo, 2020), reduce income and wealth (Caruso and Miller, 2015; Caruso, 2017), and even increase the incidence of physical and mental disabilities (Carrillo, 2020).

This has motivated a growing body of research to explore the dynamics of these far-reaching consequences. Most of these studies have focused on postdisaster damage to children's cognitive development, which is a strong predictor of school success. For example, using Mexican data, Aguilar and Vicarelli (2022) found that exposure to El Niño-related rainfall shocks in utero and during the first two years of life could translate into lower cognitive development as early as two years of age. Similarly, Rosales-Rueda (2018) studied the El Niño phenomenon in Ecuador and showed that children affected by floods in utero exhibit poor vocabulary development until age 6. Leight et al. (2015) indicated that adverse rainfall shocks during the early stages of life could reduce Chinese students' test scores by the ages of 9–12, but that this effect somewhat weakened by the ages of 17–21. In addition, some studies have presented evidence of the impact of weather shocks that have been experienced during school years. For example, Sacerdote (2012) highlighted that student evacuees from hurricanes in the US suffered sharp declines in their test scores one year after the disaster yet were able to improve their academic performance three and four years later. In contrast, Shah and Steinberg (2017) showed that positive rainfall conditions could increase wages, which translates into decreased reading and math scores of rural Indian children between the ages of 5 and 16, as these children are more likely to drop out of school in order to take on productive work.

In this paper, we explore how floods affect school-aged children's cognitive development and the potential channels of these impacts. Our contributions to the literature are as follows.

First, previous studies have tended to focus on examining how natural disasters exposed at different ages, such as in utero, during the first two years of life, and at school-going ages, are likely to affect children's later-life outcomes. However, these studies did not test whether the shorter-run damages of disasters on children are mitigated or aggravated in the longer run. Therefore, this study helps to fill this gap by comparing the short- and long-term effects of disasters on children's cognitive development as well as the channels of this impact, namely, education, time allocation, and consumption.

Second, the recent literature has attempted to identify the heterogeneity of disaster damage across gender, principle household production activity (farm versus nonfarm), caste group, location (rural versus urban), and age at time of disaster experience (see Appendix A). Nevertheless, existing empirical works have not explored the differential effects of birth order and ethnicity. In developing countries, poor parents commonly send earlier-born children to the labor market to increase the household income and finance the education of later-born siblings. When household resources are differentially allocated depending on birth order, it affects both educational attainment and the cognitive development of the first-born relative to that of later-born children. In addition, ethnic minority populations are more vulnerable to damage from disasters. This can be attributed to the limited access of such populations to public services (e.g., health care, education, electricity, clean water, etc.) and poor transportation infrastructure preventing disaster relief aid from arriving in a timely manner. Therefore, it is plausible to assume that the degree to which natural disasters negatively affect children's cognitive abilities may depend on birth order and ethnicity. This paper, hence, provides empirical evidence on the heterogeneous disaster impacts by birth order (first-born versus later-born children), ethnicity (minor versus major ethnic groups), gender and age (older versus younger children).

Third, several studies also provide evidence of the possible channels through which disasters can affect children's outcomes. However, most of these studies only tested a limited number of channels. For example, using data from Ecuador, Rosales-Rueda (2018) investigated the intermediate impact of floods on health at birth and on family inputs to skill formation, such as household income, consumption, and breastfeeding. Aguilar and Vicarelli (2022) studied income, food consumption, diet composition, household members' health, and medical expenditure to identify the channels that might translate the rainfall shock into the effects on children's physical and cognitive development in Mexico.

Another strand of literature focused on exploring how parental investments in their children's human capital change in response to the income reductions caused by natural disasters. According to these studies, one of the more important mechanisms is the household decision regarding a child's school and work participation (i.e., whether to send the child to school, to work or both). For example, Shah and Steinberg (2017) used data from rural India to test whether rainfall shocks can cause substitution away from schooling to child labor.

Björkman-Nyqvist (2013) suspects that the poor academic performance of girls in Uganda might be a result of those girls who remain in school after a negative rain shock needing to spend more time on domestic chores. It is plausible to assume that children are likely to quit school due to floods, but even if they do not have to leave school, their cognitive development becomes negatively affected because they have to spend less time studying due to longer working hours. Thus, it is important to examine the various related educational channels influenced by floods, which are likely to affect a child's cognitive skills. This paper focuses on school enrollment, grade attainment, and time allocation between study (home study and school study) and work (domestic task time and outside work time).

To investigate the effects of floods on school-age children's cognitive skills, we use data from the Young Lives study in Vietnam, which tracks the development of 3,000 children over 15 years. Using item response theory (IRT) models, we generated standardized Peabody Picture Vocabulary Test (PPVT) scores to measure children's receptive vocabulary and employed a panel fixed effect model for our empirical framework. We highlight three findings. First, floods imposed negative impacts on children's cognitive skills in the short run, but these impacts would be mitigated in the long run. Second, child schooling, child time allocation between school and work, and household food consumption (child nutrition) are the key drivers behind these effects. Third, girls, older children, firstborn children, and children from ethnic minority groups are among the groups that are more vulnerable to the negative impacts of flooding. Notably, minority children appear to be most adversely affected in the dimension of cognitive function.

The remainder of this paper is constructed as follows. Section 2 explains the models and datasets used in the analysis. Section 3 interprets the estimated results to develop comprehensive insights into the short- and long-term impacts of floods and their underlying channels. Finally, Section 4 provides concluding remarks with policy implications for designing potential alleviation policies.

2. Model and Data

2.1. Model

To understand how and why a weather shock experienced during childhood could have considerable consequences that persist even later in an individual's life, we first present a conceptual framework that has been developed in previous theoretical work on skill formation (Cunha and Heckman, 2007; Cunha et al., 2010). Following the analysis of Aguilar and Vicarelli (2022), their model suggests that a shock in early life would exert lasting effects on skills through two possible channels: a biological (direct) channel and an investment channel.

In our model, the biological channel refers to the impacts of stress or the physical conditions in which children are being raised at the time of the shock. The investment channel represents the intrahousehold reallocation of resources in response to the shock. This study investigates the impacts of floods on parental investments in skill formation. In particular, we explore the effects on household consumption, children's schooling, and time allocation.

Household consumption, which is determined by household income, is an essential input into child skill formation. A decrease in household expenditure could disrupt a child's physical and cognitive development through poor nutrition. We assume that a weather shock (i.e., flooding) leads to the contraction of consumption by decreasing household income. In this study, we separately consider flood effects on food and those on nonfood consumption. We expect that nonfood consumption is more negatively affected, as this is usually the first portion of household consumption to be reduced.

The disruptions that a negative income shock can cause during school-years have the potential to impact educational investments, which subsequently affects the development of later skills. We explore two decisions pertaining to educational investment: child schooling and child time allocation. First, we assume that a weather shock could delay children's formal education since parents are forced to withdraw them from school to reduce education expenditure. Second, in Vietnam, it is common that children only attend school for half of the day and spend most of their time after school assisting in domestic tasks such as food preparation, fetching water, washing clothes, and taking care of other members. Therefore, even children who remain in school are negatively affected by floods when they must bear the bulk of the additional work required at home because their parents are working outside the household to compensate for income loss. Thus, we expect that a weather shock could result in a reallocation among affected children of time from educational activities to labor.

This study examines the effects of floods on school-aged children and the potentially important channels through which floods may affect their cognitive ability. Based on a fixed effects model, we formulate the following equation as our base model.

$$Y_{i,t} = \alpha_0 + \beta_1 flood1_{i,t} + \beta_2 flood3_{i,t} + X'_{i,t}\gamma + \theta_t + \varepsilon_{i,t} \qquad (1)$$

where i and t denote the individual and the survey year, respectively. Y_{it} corresponds to children's cognitive achievement and the indicators of the potential channels under analysis, including children's school enrollment, their satisfactory progress (using "on track" as an indicator of school grade attainment), total hours spent in a typical day on educational activities (at school and after school), labor activities (domestic tasks and paid jobs), and household monthly food and nonfood consumption. We assume that floods exert immediate and persistent effects on the development of children. Thus, we use a dummy variable to represent flood experience in the current year, $flood1_{i,t}$, to capture the short-term impact, and a dummy variable to represent flood experiences during the three years prior to the current year, $flood3_{i,t}$, to capture the long-term impact. $X'_{i,t}$ is a vector of background characteristics. θ_t is a survey-round fixed effect to control for variables common to all children in a specific survey round. $\varepsilon_{i,t}$ is a random error term.

To capture the potentially heterogeneous effects, we augment Equation (1) by adding the interaction terms of $flood1_{i,t}$ and $flood3_{i,t}$ with a dummy variable to represent the selected individual or household factor ($Z_{i,t}$). We assume that the degree to which floods affect children's outcomes depends on their gender, birth order, age, and ethnicity. The driving channels of these heterogeneities are also analyzed. The following specification is used for this analysis.

$$Y_{i,t} = \alpha_0 + \beta_1 flood1_{i,t} + \beta_2 flood3_{i,t} + \beta_3 flood1_{i,t} \cdot Z_{i,t} + \beta_4 flood3_{i,t} \cdot Z_{i,t} + X'_{i,t}\gamma + \theta_t + \varepsilon_{i,t} \quad (2)$$

For the impact by gender, we assume that girls are more negatively affected than boys. In Vietnam, families rely on their children as a source of income during their old age. In a society where patrilocal norms still exist, households consider that a boy's financial contribution to the household will be larger than that of a girl, when they become adults. This might be because the daughter will eventually marry and leave the family while the son will remain. Hence, parents often perceive that their returns on educational investments will be higher for boys than for girls. Consequently, they tend to respond to a negative shock by reducing the resources allocated to girls to protect their investment in boys' education.

Birth order also plays a significant role in intrahousehold investments in children (Patrick and André, 2008). In Asian countries, the first-born child is often perceived as more responsible for the family than later-born children. Therefore, parents often expect their first-born child to remain in the family as an adult and to financially support all family members, whereas their later-born children are more likely to move out. Given that parents tend to invest in those children with the highest potential return, the firstborn may receive a greater share of household resources, such as more time for education. This investment can have spillover effects on later-born children, as the first-born child can tutor their younger siblings at home. On the other hand, the firstborn may work as a child laborer to financially support their family due to their higher level of responsibility to the family. The income the first child earns might then be used to finance the education of younger siblings. Accordingly, we expect that the negative effects of floods are more pronounced among the firstborn in a household than they are for later-born children.

The consequence of a natural disaster on human capital formation differs depending on the age of affected individuals. Empirical evidence has shown that the youngest children are the most vulnerable group (Caruso, 2017). The reason for this is that younger children are more likely to experience acute illnesses and posttraumatic stress symptoms, which represent the biological channel. On the other hand, the investment channel suggests that older children are more affected. This is because older children are able to obtain higher wages than their younger siblings and are thus more likely to engage in paid activities. In this study, we focus on children of secondary school ages (i.e., age 12 to 15) who are capable of joining the formal labor market from the age of 15. Therefore, parents are more likely to withdraw older children from schools and send them to full-time jobs outside the household, while younger children devote their labor to household chores. Accordingly, we assume that the investment effect outweighs the biological effect, i.e., the consequences of floods are more pronounced among older children.

The cultural communities of Vietnam are diverse, officially comprising 54 ethnic groups. The Kinh community is the major ethnic group, accounting for over 86 percent of the population (Phung et al., 2016). We expect that children in ethnic minority households are more adversely affected by floods than those in Kinh households. This might be because ethnic minorities have limited access to basic social needs (e.g., clean water, sanitary latrines, electricity, etc.). Additionally, they mainly reside in remote mountains and highlands with poor physical infrastructure (Phung et al., 2016). Therefore, floods would be more likely to cause road and school destruction in these regions, preventing minority children from going to school and receiving timely disaster relief aid.

2.2. Data and variables

2.2.1. Data sources and variable explanation

The data used in this paper come from Young Lives, a longitudinal study of childhood poverty that has collected data on two cohorts of children – one born in 1994/95 and another born in 2001/02 – in four developing countries since 2002. We use data on the 2001/02 cohort from the last two survey rounds in Vietnam completed in 2013 (R4) and 2016 (R5). This survey followed a multistage sampling procedure. First, four sentinel communes were selected in each of the five chosen provinces using an over-poor sampling rule based on poverty rankings. The additional communes, 11 communes in total, were chosen based on the other criteria[1] (see Figure 2). As a result, 31 communes were involved in the initial study sample. Fifteen out of those communes comprise the poor group (48%), while nine and seven comprise the average group (29%) and the above-average group (23%) respectively. In each commune, 50 households with at least one child of age 8 or over and 100 households with at least one child

[1] The over-poor sampling strategy proceeds as follows: two communes from the poor group, one from the average group, and one from the above-average group are selected. Other criteria to choose additional communes include: (1) that the commune should represent common provincial features, (2) a commitment from the local government for the research, (3) feasibility conditions with respect to the research logistics, and (4) population size.

of age 1 or over were randomly enrolled. Although the sample contains a higher percentage of poor households, comparisons with nationally representative datasets reveal that it provides rich information on a large range of living-standard conditions in Vietnam (Nguyen, 2008).

[Insert Figure 2 here]

The primary outcome variable is the Peabody Picture Vocabulary Test (PPVT) score, which captures cognitive achievement. The test has been widely used to measure receptive vocabulary by asking children to indicate the picture that best describes the meaning of a stimulus word. Empirical evidence also suggests that receptive vocabulary strongly correlates with several measures of general intelligence and contributes directly to school success (Cueto and León, 2012). Therefore, we employ PPVT to capture the cognitive achievement of children and adopt the item response theory (IRT) method to construct composite scores for PPVT. The use of IRT models is standard in education assessments due to its significant advantages over the use of raw aggregates for all subitems. While using the raw aggregates of correct answers assumes that the difficulty is the same across all questions, the IRT method allows for taking into account the different level of difficulty of each question in a test. It also enables the computation of scores from repeated tests over time on a common scale (Singh, 2015). Using IRT, we estimated a three-parameter logistic model for the probability of a correct response by an individual to the different test questions. The three parameters used are item discrimination, item difficulty, and the possibility of randomly guessing an item[2]. Using these parameters, we calculated z scores representing children's composite scores for PPVT[3].

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[2] For a detailed explanation of IRT models, please refer to Van der Linden and Hambleton (1997) and Das and Zajonc (2010).

[3] We used the OpenIRT suite of commands in Stata developed by Tristan Zajonc to generate the maximum likelihood scores used in this analysis. A core assumption of IRT models is that item parameters do not significantly differ across groups. This assumption cannot be maintained across different languages as difficulty levels may plausibly change during translation. Therefore, we were constrained to only use the scores of children who took the tests in Vietnamese. We then normalized the scores by cohort to have a mean of 0 in the first period in which the test is administered (Round 2).

To investigate whether a temporary delay in the formal education of children occurs due to floods, we use the following outcome variables. The first is a binary variable that takes the value 1 if the child is currently enrolled in formal school. The next child schooling outcome variable is "on track", which is a measure of age-specific grade attainment. We define on track as a dummy variable that equals 1 if the value of age minus grade is 5 or under. That is, if a 7-year-old is in second and third grade, he is coded as on track, but if he is in first grade, he is not.

The Young Lives survey provides detailed information about the amount of time a child spends on different activities during a typical day, which is defined here as a weekday or a normal school day, excluding holidays, festivals, days of rest, the weekend, and so on. In this analysis, we focus on income-generating activities and human capital-accumulating activities. Our purpose is to examine the substitution of time between these two types of activities in the aftermath of floods. We first consider the flood effects on children's total time spent studying and working and then analyze the impacts on time allocated to specific activities for each purpose. Specifically, child labor activities include home production and paid jobs outside of the household, while educational activities consist of formal studying time both at school and after school (e.g., homework or classes and tutorials outside school class hours).

To capture household economic situations, consumption is considered to be a better measure than income, especially in developing countries. This is because income tends to vary with season. In particular, problems such as a month with no income may arise if the survey month differs across regions. In contrast, consumption can be smoothed out in the long term through savings, hence allowing us to more accurately analyze the impact on household finances. Therefore, we aggregated the total monthly values of household expenditures grouped by food items and nonfood items and calculated real consumption using the Consumer Price Index (CPI). Data for the CPI are collected from the General Statistics Office of Vietnam. We use the logarithm transformation of this variable in the model specification.

The key regressors of interest are self-reported flooding shocks by year during R3–R4 and R4–R5. We make use of information about the year of shocks to construct a binary variable for flood exposure during the survey year and a lag dummy variable for flood exposure over the three years prior to the survey year. Other explanatory variables used comprise household characteristics, as described in Table 1.

2.2.2. Descriptive statistics

The final sample consists of 1,429 children aged approximately 12 and 15 years for each round. Table 1 presents the information on certain basic characteristics of our studied sample. The average IRT PPVT score of children is 2.567 standard deviations (SDs). A large proportion of children are currently enrolled in school and have completed the grade appropriate for their age, at approximately 89.6 percent and 81.4 percent, respectively. Regarding time allocation, children tend to spend more time a day on educational activities than on labor activities (8 hours versus 2.2 hours). Specifically, a child spends an average of 5.3 hours at school and 2.6 hours on homework or tutorials outside of formal class hours. In contrast, they spend only 1.9 and 0.3 hours participating in home production and paid outside work, respectively.

[Insert Table 1 and Table 2 here]

Considering the economic conditions, only one in three households primarily depends on income from agriculture. In addition, households tend to spend more on food items relative to nonfood items (26.3 USD versus 23.12 USD per capita per month). These values are lower than those of the national monthly average expenditures per capita during the same period (2012–2016), which are 26.8 USD for food and 23.71 USD for nonfood consumption[4]. This indicates that our sample mainly includes low-income households in Vietnam. Among these households, more than 80 percent have access to basic social needs such as proper sanitation and formal education. However, most household heads have not completed secondary education (83.1 percent).

Only 1.8 and 1.3 percent of households in the sample reported having experienced current or past floods, respectively. We compare the outcomes of interest between households that are negatively affected and those not affected by floods in Table 2. For floods in the current year, children who were exposed appear to score lower than their peers who were not exposed. There is clear evidence that the schooling outcomes of affected children (i.e., enrollment and being

[4] We calculated the monthly average real expenditures per capita over the 2012–2016 period using data from General Statistics Office of Vietnam (2018, p.342).

on track) are worse than those of unaffected children by over 10 percent. The statistics shown in Table 2 also suggest that floods significantly caused affected children to spend 1.5 hours more time on labor activities and 1.4 less hours of time on educational activities relative to those spent by unaffected children. Additionally, households that experienced floods tend to have lower food and nonfood expenditures compared to those that did not experience floods. Considering the after-effect of past floods, we also observe similar differences but with smaller magnitudes in almost all of the outcomes between the two groups. One notable exception is the wider gaps in household consumption caused by past floods compared to floods during the survey year.

3. Empirical results

In this section, we explore the impact of floods on PPVT scores and the possible channels through which floods affect the cognitive development of children, including education participation, time allocation between study and labor, and household consumption. Table 3 reports our main estimation results. Panel A presents the model considering the effect of floods in the current year, and Panel B presents the model that captures the effects of both past and contemporaneous floods.

3.1. Possible channels of flood effects on children's cognitive ability

3.1.1. Household consumption

Households can experience considerable income losses in response to shocks because of poor crop yields. The reduction in income could translate into a decline in consumption when households are unable to cope with such a reduction. We examine household consumption responses to floods in Columns 6 and 7 of Table 3. The estimates of floods in the current year (current floods) are insignificant for both types of expenditures, whereas those of floods from four to one year ago (past floods) are significant for food but not for nonfood consumption. The results indicate that households exposed to such shock do not experience significant changes in nonfood expenditures over both the short and long term. In Vietnam, households spend more than half of their total expenditure on food consumption. In addition, approximately two-thirds of their nonfood consumption is spent on fundamental needs such as housing, electricity, water, sanitation, health care, education, travel, and communication[5]. Therefore, households tend to reduce food consumption more than nonfood consumption as a means of coping with income shocks.

In contrast, we observe contractions in the value of food consumption of 14.5 percent due to past floods, although the immediate impact of current floods is insignificant. One possible explanation is that food assistance from the Vietnamese government is provided to affected households for only a short period of up to three months during and after natural disasters (Decree 136/2013/ND-CP[6]). Thus, the negative impact on food consumption temporarily disappeared during the flood year but appeared again after one or two years following the cessation of government support. This implies the negative effect of floods on household income in the long run since consumption decisions are greatly dependent on income constraints.

[Insert Table 3 here]

These results suggest that in the period of an excessive rainfall shock and hence, low agricultural income, households are forced to reduce the money spent on food consumption as a long-term adaptation, often by adopting changes in their diet or even by reducing the amount of their food intake. Overall, the decline in household food consumption can contribute to poor childhood nutrition, which can have negative consequences on the brain development and cognitive functions of young children.

3.1.2. Children's schooling

Columns 2 and 3 of Table 3 show that flooding in the current year significantly affects both school enrollment and on-track status. The dummy of current floods is estimated to be

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[5] We calculated the percentage of food consumption in total expenditure for living and the percentage of spending on fundamental needs in nonfood consumption using data in the year 2016 from General Statistics Office of Vietnam (2018, p. 344, 363, 364).

[6] For the details of this Decree, please access the following website (only in Vietnamese): https://vbpl.vn/bolaodong/Pages/vbpq-van-ban-goc.aspx?dvid=318&ItemID=32529

statistically significant and negative for both outcomes. This implies that children affected by contemporaneous floods are 13.6~14.1 percentage points less likely to be enrolled in school than unaffected children. Likewise, these children are 15.8~16.2 percentage points less likely to be on track. However, we do not find statistically significant estimates for the effect of past floods. Our results are consistent with the credit constraints explanation provided by Zimmermann (2020). An extreme rainfall shock lowers household income by causing extensive damage to crops. Consequently, children may have to drop out of school due to a lack of household resources, which disrupts their human capital accumulation.

3.1.3. Children's time allocation

In Columns 4–5 of Table 3, we examine the reallocation of children's time between labor and educational activities in response to changes in economic conditions due to floods. The results of time use for specific activities, including studying at home and school as well as working on domestic tasks and outside jobs, are reported in Table B1 (Appendix B). The dummy of current floods is significantly negative for total study time but is significantly positive for total work time. The estimates indicate that exposure to floods in the current year is associated with a reduction in the amount of time spent studying and an increase in the amount of time spent working. Analysis of specific activities shows that this time reduction mainly occurs at school, while study time at home appears unaffected. On the other hand, the coefficients for both time uses on domestic tasks and outside work are significantly positive, implying that current floods could increase the time of all child labor activities.

Regarding past floods, we obtain similar results for total study time as in the case of current floods. Although the dummy of past floods for total work time is insignificant, estimations in Table B1 show a significantly positive coefficient of this dummy variable for domestic task time. These results suggest that the adverse impacts of floods on total study time persist in the longer run. Floods increase the time spent on home production in both periods, although past floods do not affect the total labor time of children. Considering the magnitude of these effects, being affected by floods in the current year is associated with an average reallocation of approximately 1.527 hours per day away from educational activities toward labor activities (0.717 hours to domestic tasks and outside work). Approximately 1.539 hours per day are allocated away from time spent studying to other activities due to past floods, nearly 60 (=0.891/1.539) percent of which are spent on household tasks.

These findings imply that households respond to income shocks by reducing their investments in human capital and increasing their children's participation in home production. As a result, children are forced to miss school often and eventually drop out of school. This reallocation is consistent with the precautionary mechanism explained by Colmer (2021), which assumes that households tend to engage in precautionary savings as a response to income uncertainty.

3.2. Flood effects on children's cognitive ability

Column 1 in Table 3 presents the estimated effects of exposure to floods on children's vocabulary test scores calculated using IRT. The estimates suggest that exposure to floods in the current year decreases IRT PPVT scores by 0.302 to 0.307 SDs on average. However, the dummy of past floods is negative but insignificant, which may be affected by the small number of households damaged by floods. However, as discussed above, past floods imposed adverse effects on households' food consumption and children's time allocation. Therefore, floods are likely to exert negative impacts on children's cognitive ability over both the short and long term, but the long-term effect is smaller than the short-term effect.

These findings differ from those of recent studies that emphasize the long-term impacts of early childhood weather shocks on cognitive performance. For example, using data from China, Leight et al. (2015) identified that a 1 SD increase in rainfall between in utero and the first two years of life is associated with a 0.056 to 0.133 SDs decrease in cognitive test scores when children were 9–12 years old. To examine the impacts of the 1997–1998 El Niño event on cognitive development, Rosales-Rueda (2018) analyzed Ecuadorian data and found that children exposed to severe floods in the first trimester of pregnancy score 0.1 SDs lower on PPVT at ages 3–6. Similarly, Aguilar and Vicarelli (2022) indicated that excessive rainfall shocks due to El Niño during the early stages of life reduced the language development, working memory, and visual-spatial thinking test scores of Mexican children between 2 and 6 years of age by 0.19, 0.17, and 0.15 SDs, respectively. Overall, the previous literature has argued that in utero and early childhood (up to age 2) are the critical periods that are most sensitive to the persistent effects of stressful weather conditions. In contrast, our study seeks to compare the short- and long-term consequences of natural disasters (i.e., floods) experienced by school aged children and provides evidence of stronger negative effects in the short term (approximately 0.3 SDs) than in the long term.

[Insert Figure 3 here]

As explained above, the use of the IRT method provides a more accurate measurement of test takers' ability than the use of the raw aggregates of all questions. To illustrate this difference, we compare the estimated coefficients of flood effects between the IRT and raw scores. Figure 3 shows that estimations using raw PPVT scores present a more minor negative impact of floods on children's cognitive skills than those using IRT. Specifically, floods in the current year decrease IRT PPVT scores by approximately 14 percent while reducing raw PPVT scores by only approximately 10 percent. On the other hand, the effect of past floods is consistently insignificant in both measurements. Our findings show that the results of previous studies using raw test scores are likely to underestimate the short-term impact.

3.3. Heterogeneous effects

Now that we have shown the negative effects of floods on children's cognitive skills, it is plausible that certain socioeconomic groups were potentially able to mitigate these negative repercussions. To delve into the heterogeneity of flood impacts, we consider gender, birth order, age, and ethnicity as different proxies capturing the level of socioeconomic inequality among affected children. We then explore the possible channels accounting for these differential effects.

3.3.1. Gender

Table 4 shows that the cross terms of the male dummy with the dummies of current and past floods are significant in the IRT PPVT model. We found that there was no significant difference between the impacts on cognitive ability for boys and girls, although floods reduce the PPVT scores.

[Insert Table 4 here]

The results displayed in Columns 2 and 3 indicate that floods do not exert impacts on school enrollment for both boys and girls in the short term. However, it negatively affects only girls in the long term. Concerning on-track effects, the effects of floods are significant and identical to the negative sign between sexes in the short term. Nevertheless, they are significantly negative only for girls in the long term. Therefore, there is a gender difference regarding the long- but not the short-term consequences of education participation. This may be because all children have to drop out of school in favor of child labor to support the family right after the flood, but once all children are no longer required to support their household in the process of recovery, parents tend to choose girls' support.

Regarding children's time allocation, Columns 4–5 show that both genders tend to decrease their time spent studying and increase their time spent working during the flood year. Nonetheless, in the long run, girls still have to spend less time studying, while boys are likely to recover, as shown in Column 1 of Table B2 (Appendix B), which indicates that this heterogeneous influence is statistically significant only for study time at home. This implies a gender difference for time allocation in the long term but not the short term, as in the case of enrollment and on-track status.

The results suggest that households respond to negative income shocks by reducing the education opportunities provided to girls to make them work more, while boys are, to a large extent, sheltered from this. There are two possible explanations for the differential investment by gender in education and time allocation. First, in countries where child labor is widespread, girls are viewed as more productive than boys in household chores. Although biological conditions might suggest that sons are stronger and thus more able to perform certain household tasks, daughters are often viewed as being better substitutes for mothers in taking care of siblings and other domestic tasks such as cleaning or cooking. Therefore, girls must bear the bulk of the additional work required at home when the parents are working outside the household to cover income losses. Second, households often perceive that a boy's contribution to the household as an adult will be larger than a girl's contribution since the girl will eventually marry and leave the natal home while the son will likely remain in the family. Hence, parents are inclined to withdraw girls from school to protect their investment in boys' education during periods of insufficient income.

3.3.2. Birth order

Table 5 presents the heterogeneous effects of exposure to floods by birth order. We find that the cross term of the later-born dummy with flood dummies is not significant but positive for IRT PPVT. The small number of observations of households damaged by floods is likely to lead to insignificant results since the impacts on education participation and the time allocation of later-born children are significantly smaller, as explained later. Therefore, the negative impact of floods on the cognitive ability of later-born children is likely to be smaller than that of first-born children.

[Insert Table 5 here]

The role of birth order in the allocation of household resources to children can explain these differential effects. We obtain significantly positive estimated coefficients for the cross term of the later-born dummy with the current flood dummy in the enrollment, on-track status, and total study time models. Regarding the magnitude of impacts, the results in Columns 2 and 3 indicate that the later-born children are 25.9 percentage points more likely to enroll in school and approximately 24 percentage points more likely to be on track than the first-borns immediately after experiencing floods. Furthermore, Columns 4–5 also highlight a difference in favor of later-born children. During flood year, households tend to allocate approximately 1.9 hours more time spent studying to the later-born children than to firstborns, although they reduce the total study time of both groups. This difference mainly occurs for hours spent at school, as presented in Table B3. However, the birth-order difference in study time is not persistent in the long run.

Here, we observe that the reallocation of time associated with floods is likely to disadvantage first-born children to a greater degree. Furthermore, although all children experience a decrease in the time they spend studying in both the short and long term, the labor activity to which this time is possibly reallocated tends to vary over time, as shown in Table B3. In the short term, when a family is forced to seek alternative income-generating activities, the time taken from children's schooling is mostly spent on outside work. However, in the long term, when the family needs additional labor to replant crops, reraise livestock, and reconstruct the damaged facilities of the family business, this time is entirely spent on home production.

Our results imply that the first-born child is more sensitive to the consequences of floods than the later-born child. This is possibly because first-born children are more responsible for their families than later-born children. Therefore, the firstborn is more likely to drop out of school and engage in work activities when households experience income reductions. Moreover, the additional income generated by the first-born child can be used to finance the education of younger siblings, which can offset the damage exerted by floods on later-born children.

3.3.3. Age

Table 6 explores the heterogeneity in flood effects across age groups. We observe a negative effect of current floods on cognitive outcomes. Immediately after being exposed to floods, children score 0.291~0.314 SDs lower on cognitive test scores than nonaffected children (see Column 1). However, we cannot provide clear evidence on the age-specific effects of contemporaneous floods since the interaction term with the age dummy is insignificant.

[Insert Table 6 here]

Columns 2–5 suggest that the potential channels behind this effect are related to parents responding to adverse income shocks by allocating fewer resources to their children. The dummy of current floods is significantly negative, but its cross term with the age dummy is insignificant for all channels considered, meaning there is no age heterogeneity in the impacts of current floods. On the other hand, both the single term and the interaction term with the age dummy of past floods are not significant in all models. However, the results in Table B4 (Appendix B) indicate that flood experiences in previous years significantly increase domestic task time while decreasing the outside work time and school study time of children. Although past floods exert impacts on work activities in opposite directions, the point estimate for total work time is positive, meaning that past floods are likely to increase the time allotted for children's labor. We also obtain statistical evidence supporting the different impacts on domestic task time between younger (age 12) and older (age 15) children in both the short and long term. We found that children were unlikely to go to school and be on track as a result of floods in the current year. At the same time, they are forced to decrease their time spent studying and increase their time spent working in both the short and long run.

While all children increase the time allocated for working after floods, parents' decision on which type of work children will spend more time on depends on age and the time of flood exposure. Columns 3 and 4 in Table B4 provide clear evidence for this finding. Floods in the current year increase the time spent working on paid jobs outside the household of all children by 0.9 hours. On the other hand, the significant and positive cross term of the current flood dummy with the age dummy indicates that the time allocated for domestic tasks is also increased for younger children. The results suggest that younger children bear extra domestic work that has generally been the responsibility of older children since the older children tend to work more outside the home than the younger children. Four years after the shocks, the family reallocates their older children's labor from outside work back to home production, possibly due to the increased labor demand needed to restart temporarily delayed production. This finding is depicted by a 1.7-hour increase in the time that older children spent on home production and a 0.8-hour decrease in the time that they spent on outside work due to past floods. As explained above, parents tend to assign more work to older children because they are often viewed as more productive, more reliable, and better able to perform more complex tasks. Therefore, younger children spend 1.4 hours less time working in home production than older children, although all children increase their involvement in this activity.

3.3.4. Ethnicity

Estimation results for the differential impacts of floods across ethnicities are reported in Table 7. As expected, floods in the current year adversely affect child cognitive performance regardless of ethnicity. However, the negative effect is greater for minority group, whose scores are approximately five times lower than that of the Kinh group. These results are presented by the significant estimations for the current flood dummy and its interaction term with the minority dummy.

[Insert Table 7 here]

This difference is due to ethnic minority households having fewer resources to invest in children than Kinh households. Specifically, the dummy of flood in the current year is not significant, but its cross term with the dummy of the minority is significant and negative for both food and nonfood consumption. This implies that floods have a stronger negative impact on minority households' expenditures in the short term. Therefore, ethnic minority children are more likely to be undernourished, which can delay physical development and impair cognitive function. Interestingly, Column 6 shows that the past flood dummy is significantly negative, and its cross term with the minority dummy is significantly positive with a greater magnitude, meaning that the short-term impact of floods on the minority's food consumption is fully mitigated in the long term. This is possibly because disaster relief aid (mainly food aid) in Vietnam tends to prioritize disadvantaged populations such as ethnic minority groups, thus helping to increase the speed of their recovery after shock.

In addition, minority children have to work more than Kinh children right after experiencing floods, mainly in home production. This finding is supported by the significantly positive coefficients for the cross term of the current flood dummy with the minority dummy in Column 5 of Table 7 and Column 3 of Table B5. Moreover, this differential effect is likely to persist in the long run since the cross term of the past flood dummy is significant for domestic task time despite being non-significant for total work time. Specifically, floods in the current year increase the time spent on domestic chores for all children; however, the minority children tend to work 3.2 hours more than the Kinh children. Although floods in the past years exerted no effect on Kinh children's labor time, minority children are forced to spend 2.6 hours more time on household tasks than their Kinh peers. In addition, the results in Columns 2–5 indicate that floods in the current year adversely affect educational outcomes (i.e., enrollment, on-track status, and total study time), in which the effects on total study time are likely to persist for several years, but there is no significant ethnic heterogeneity.

We suppose that households of ethnic minorities are more adversely affected by floods because they have substantially lower incomes than Kinh households. The huge income gap between the Kinh and ethnic minorities is well established in studies on poverty in Vietnam (Badiani-Magnusson et al., 2012). Furthermore, ethnic minorities rely heavily on agricultural income, while Kinh tend to be engaged in nonfarm production and business. Therefore, minority households are more vulnerable to natural disasters. In addition to the income gap, another channel that could explain our results is the lack of physical infrastructure. A large population of ethnic minorities resides in the mountains and highlands, where access to basic social needs (e.g., clean water, sanitary latrines, electricity) and physical infrastructures are poor. Therefore, roads and schools in these areas are more likely to be destroyed by floods, which makes children unable to attend school and disaster relief aid unable to arrive in a timely manner.

3.4. Placebo test

To verify that our results are not confounded by a trend or omitted variables, we perform a set of randomization tests following Hsiang and Jina (2014). Holding the observations of other variables fixed, we randomize observations of current and past flood experiences 10,000 times, each time re-estimating Equations (1) ~ (2) using these placebo realizations of flood experiences. We then plot the distribution of each estimated coefficient and compute an exact p value as the share of placebo β's that have higher absolute values than the estimate of β using the original data. We implement this randomization through three different approaches as follows.

1. Entire sample – We randomly reassign each flood experience observation.
2. Between children – We randomly reassign each child's complete history of flood experiences to another child while preserving the ordering of years.
3. Within child – We randomly reorder each child's time series of flood experiences while keeping each assigned to the original child.

[Insert Figures 4 and 5 here]

We present the results of our placebo test only for the dummies of current and past floods and their cross terms with the dummy of minority for IRT PPVT in Figures 4 and 5, respectively, due to limited space. The results using the dummies of male, later born, and age are reported in Appendix C and those for the other outcome variables are shown in Appendix D. It should be noted that we report the main results of only the first two approaches[7] since the third approach does not provide meaningful results. This is because our sample's number of observations of flood experiences is very small (approximately 1 percent). Thus, the data created by reordering each child's time series of flood experiences are not overly changed under the third approach.

In Figures 4 and 5, the distributions of point estimates are symmetric around zero in all plots, implying that the models in Equations (1) ~ (2) are unlikely to produce biased results for IRT PPVT, as explained by Hsiang and Jina (2014) and Colmer (2021). For the placebo test, we primarily focus on the significant parameters of the original estimation. Figure 4 shows that the p value of the current flood dummy in the baseline model is below 0.05, suggesting that our original parameter is unlikely to occur by chance at 5 percent. In contrast, Figure 5 depicts that the p values of the current flood dummy and its cross term with the minority dummy exceed 0.05 but remain below 0.1, indicating that these estimates are unlikely to occur by coincidence at 10 percent, but this result may not be robust.

For gender, birth order, and age heterogeneity of IRT PPVT, all figures shown in Appendix C again confirm that the models in Equations (1) ~ (2) are unlikely to produce biased results for IRT PPVT as above. In addition, the p values of the current flood dummies used in the gender and birth order heterogeneity models remain below 0.05 in all cases, supporting the premise that these parameters are unlikely to occur by chance. On the other hand, the p value for the single term of the current flood dummy in the age heterogeneity model is above 0.05 but below 0.1 for the entire-sample randomization of Panel A and the between-children randomization of Panel B. This implies that these estimates are unlikely to capture spurious correlation at 10 percent, but the result may not be robust. In addition, we find that the p value for the single term of the current flood dummy in Panel B of the age heterogeneity model

[7] The results for the third approach are available upon request.

exceeds 0.1 for entire-sample randomization. Hence, we cannot reject the possibility that this parameter is obtained by coincidence, even at 10 percent.

All other results are reported in Appendix D. We confirm that the models in Equations (1) ~ (2) are unlikely to produce biased results. The p values are above 0.1 for the cross term with the minority dummy of past flood dummy in food consumption and domestic task time models and that of the current flood dummy in the nonfood consumption model for either entire-sample or between-children randomization. Thus, these original parameters are likely to capture spurious correlations. Nonetheless, the p values of other coefficients indicate that their original estimates are unlikely to occur by chance at 10 percent.

4. Conclusion and policy implications

This study contributes empirical evidence to the literature regarding the short- and long-term impacts of natural disasters – specifically flooding – on the cognitive skills of school-aged children and the possible channels for these effects of education participation, time allocation, and consumption. We confirm that floods immediately decrease children's cognitive abilities and education opportunities, reduce their available studying time, and increase their working time. While previous studies only consider the impact on school enrollment in general, we provide new evidence on the many important aspects of child education and find that floods not only force children to drop out of school but also reduce the time spent studying at school for those children who remain in school. In addition, we find that floods increase the time spent working on both domestic tasks and outside paid jobs, whereas existing studies only focus on whether floods affect children's participation in the labor force. In the long run, the impact on the PPVT score is insignificantly negative. However, our results highlight that floods tend to lower food consumption and increase the reallocation of children's time from study to labor activities. Therefore, the long-term impact on the PPVT score is likely to be negative. Through the other channels assessed, floods seem to exert no significant long-term effects.

Compared to the results of previous studies that emphasize the long-run consequences of natural disasters experienced either in utero or in the first two years of life, we find a stronger negative effect on cognitive skills in the short run for children experiencing disasters during school ages (age 9–15). The results suggest that not only children in the early stage of life but also school-aged children are in need of disaster relief aid, especially immediately after exposure. Interventions that boost income and increase access to insurance against disaster risk are likely to mitigate the negative impacts of floods on children.

Moreover, we explore how children are differently affected by floods and uncover new evidence for the heterogeneous impacts of ethnicity and birth order. Specifically, in the short term, we find a differential impact on PPVT by ethnicity. Additionally, we find weak (insignificant) evidence that the negative impact on PPVT for first-born children is likely to be more substantial than that for later-born children. The results for educational outcome indirectly support this finding, as the negative impact on education and the positive impact on working hours are significantly larger for firstborns. For educational outcomes (enrollment, on-track status, and time spent studying), there is heterogeneity to flood effects by birth order but not by other factors. Concerning time spent working, there is a differential impact by ethnicity and age but not by gender or birth order. We also observe the heterogeneous effect of ethnicity on household consumption. In the long term, we find evidence of a differential impact on educational outcomes by gender and ethnicity but not by birth order or age. The results also indicate heterogeneity by age and ethnicity regarding working hours. Similar to the short-term effects, there is an ethnic difference in the impacts on consumption.

These findings highlight that girls, older children, firstborns, and minority children are more disadvantaged than other groups. In particular, the negative impacts on cognitive skills are greater for minority children than for their Kinh peers. This is because ethnic minority households may have fewer resources to invest in their children compared to Kinh households. Additionally, our channel analysis indicates that school enrollment and the resources provided to girls, older children, firstborn children, and children from ethnic minority communities are decreased, while other groups seem to be sheltered from this effect. In addition, these children are forced to spend less time studying and more time working on income-generating activities than the other groups. Our findings suggest that policies such as social protection and safety nets need to be well targeted to these children, with a special focus given to ethnic minority populations.

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References

Adhvaryu, A., Nyshadham, A., Molina, T., & Tamayo, J. (2018). Helping Children Catch Up: Early Life Shocks and the PROGRESA Experiment (Working paper No. 24848). National Bureau of Economic Research. https://doi.org/10.3386/w24848.

Aguilar, A., & Vicarelli, M. (2022). El Niño and children: Medium-term effects of early-life weather shocks on cognitive and health outcomes. *World Development, 150,* 105690. https://doi.org/10.1016/j.worlddev.2021.105690.

Alvi, E., & Dendir, S. (2011). Weathering the Storms: Credit Receipt and Child Labor in the Aftermath of the Great Floods (1998) in Bangladesh. *World Development, 39*(8), 1398-1409. https://doi.org/10.1016/j.worlddev.2011.01.003.

Badiani-Magnusson, R. C., Baulch, B., Brandt, L., et al. (2012). Vietnam poverty assessment: well begun, not yet done – Vietnam's remarkable progress on poverty reduction and the emerging challenges. Washington, D.C.: World Bank Group. Retrieved from http://documents.worldbank.org/curated/en/563561468329654096/2012-Vietnam-poverty-assessment-well-begun-not-yet-done-Vietnams-remarkable-progress-on-poverty-reduction-and-the-emerging-challenges. Accessed August 10, 2022.

Baez, J. E., & Santos, I. V. (2007). Children's Vulnerability to Weather Shocks: A Natural Disaster as a Natural Experiment. *Social science research network*, New York. Retrieved from https://conference.iza.org/conference_files/chldc2007/baez_j3321.pdf. Accessed August 15, 2022.

[dataset] Boyden, J. (2022). *Young Lives: an International Study of Childhood Poverty: Rounds 1-5 Constructed Files, 2002-2016*. *5th Edition*. UK Data Service. SN: 7483, https://doi.org/10.5255/UKDA-SN-7483-5.

Björkman-Nyqvist, M. (2013). Income shocks and gender gaps in education: Evidence from Uganda. *Journal of Development Economics, 105,* 237-253. https://doi.org/10.1016/j.jdeveco.2013.07.013.

Carrillo, B. (2020). Early Rainfall Shocks and Later-Life Outcomes: Evidence from Colombia. *The World Bank Economic Review, 34*(1), 179-209. https://doi.org/10.1093/wber/lhy014.

Caruso, G. D. (2017). The legacy of natural disasters: The intergenerational impact of 100 years of disasters in Latin America. *Journal of Development Economics, 127,* 209-233. https://doi.org/10.1016/j.jdeveco.2017.03.007.

Caruso, G., & Miller, S. (2015). Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 Ancash Earthquake. *Journal of Development Economics, 117,* 134-150. https://doi.org/10.1016/j.jdeveco.2015.07.012.

Colmer, J. (2021). Rainfall Variability, Child Labor, and Human Capital Accumulation in Rural Ethiopia. *American Journal of Agricultural Economics, 103*(3), 858-877. https://doi.org/10.1111/ajae.12128.

Cueto, S., & León, J. (2012). Psychometric Characteristics of Cognitive Development and Achievement Instruments in Round 3 of Young Lives (Technical Note 25). Oxford, UK: Young Lives. Retrieved from https://www.younglives.org.uk/sites/default/files/migrated/YL-TN25_Cueto.pdf. Accessed August 15, 2022.

Cunha, F., & Heckman J. (2007). The technology of skill formation. *American Economic Review, 97*(2), 31-47. https://doi.org/10.1257/aer.97.2.31.

Cunha, F., Heckman, J. J., & Schennach, S. M. (2010). Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Econometrica, 78*(3), 883-931. https://doi.org/10.3982/ECTA6551.

Das, J., & Zajonc, T. (2010). India shining and Bharat drowning: Comparing two Indian states to the worldwide distribution in mathematics achievement. *Journal of Development Economics, 92*(2), 175-187. https://doi.org/10.1016/j.jdeveco.2009.03.004.

de Janvry, A., Finan, F., Sadoulet, E., & Vakis, R. (2006). Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? *Journal of Development Economics, 79*(2), 349-373. https://doi.org/10.1016/j.jdeveco.2006.01.013.

de Vreyer, P., Guilbert, N., & Mesplé-Somps, S. (2012). The 1987-89 Locust Plague in Mali: Evidences of the Heterogeneous Impact of Income Shocks on Education Outcomes (Working Paper). HAL. Retrieved from https://hal-pse.archives-ouvertes.fr/hal-00961739. Accessed August 15, 2022.

[dataset] Duc, L. T., Penny, M., Boyden, J., Woldehanna, T., Galab, S., & Sanchez, A. (2022). *Young Lives: an International Study of Childhood Poverty: Round 4, 2013-2014. 3rd Edition*. UK Data Service. SN: 7931, https://doi.org/10.5255/UKDA-SN-7931-3.

Dumas, C. (2020). Productivity Shocks and Child Labor: The Role of Credit and Agricultural Labor Markets. *Economic Development and Cultural Change, 68*(3), 763-812. https://doi.org/10.1086/701828.

Eckstein, D., Künzel, V., Schäfer, L., & Winges, M. (2019). GLOBAL CLIMATE RISK INDEX 2020. Who Suffers Most from Extreme Weather Events? Weather-Related Loss Events in 2018 and 1999 to 2018. Germanwatch e.V. Retrieved from https://www.germanwatch.org/sites/germanwatch.org/files/20-2-01e%20Global%20Climate%20Risk%20Index%202020_13.pdf. Accessed August 15, 2022.

Emerson, P. M., & Souza, A. P. (2008). Birth order, child labor, and school attendance in Brazil. *World Development, 36*(9), 1647-1664. https://doi.org/10.1016/j.worlddev.2007.09.004.

Feeny, S., Mishra, A., Trinh, TA., Ye, L., & Zhu, A. (2021). Early-Life Exposure to Rainfall Shocks and Gender Gaps in Employment: Findings from Vietnam. *Journal of Economic Behavior and Organization, 183,* 533-554. https://doi.org/10.1016/j.jebo.2021.01.016.

General Statistics Office of Vietnam (2018). Results of the Viet Nam household living standards survey 2016. *Statistical Publishing House*. Retrieved from https://www.gso.gov.vn/wp-content/uploads/2019/03/VHLSS-2016-1.pdf. Accessed March 5, 2023.

Gitter, S. R., & Barham, B. L. (2007). Credit, natural disasters, coffee, and educational attainment in rural Honduras. *World Development, 35*(3), 498-511. https://doi.org/10.1016/j.worlddev.2006.03.007.

Groppo, V., & Kraehnert, K. (2017). The impact of extreme weather events on education. *Journal of Population Economics, 30*(2)*,* 433-472. https://doi.org/10.1007/s00148-016-0628-6.

Hsiang, S., & Jina, A. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones (Working paper No. 20352). National Bureau of Economic Research. https://doi.org/10.3386/w20352.

Hyland, M., & Russ, J. (2019). Water as destiny – The long-term impacts of drought in sub-Saharan Africa. *World Development, 115,* 30-45. https://doi.org/10.1016/j.worlddev.2018.11.002.

Le, T. D., & Nguyen, T. (2014). Young Lives Survey Design and Sampling in Viet Nam: Preliminary Findings from the 2013 Young Lives Survey (Round 4) (Fact sheet). Oxford, UK: Young Lives. Retrieved from https://www.younglives.org.uk/sites/default/files/migrated/VIETNAM-SurveyDesign-Factsheet.pdf. Accessed August 15, 2022.

Leight, J., Glewwe, P., & Park, A. (2015). The Impact of Early Childhood Rainfall Shocks on the Evolution of Cognitive and Non-cognitive Skills (Working Paper No. 2016-14). Department of Economics, Williams College. Retrieved from https://web.williams.edu/Economics/wp/LeightGlewweParkImpactOfEarlyChildhoodRainfallShocksOnSkills.pdf. Accessed August 15, 2022.

Mottaleb, K. A., Mohanty, S., & Mishra, A. K. (2015). Intra-household resource allocation under negative income shock: A natural experiment. *World Development, 66,* 557-571. https://doi.org/10.1016/j.worlddev.2014.09.012.

Nguyen, N. P. (2008). An Assessment of the Young Lives Sampling Approach in Vietnam (Technical Note 4). Oxford, UK: Young Lives. Retrieved from https://www.younglives.org.uk/sites/default/files/migrated/YL-TN4-Nguyen-Sampling-Approach-In-Vietnam.pdf. Accessed August 15, 2022.

Nordman, C. J., Sharma, S., & Sunder, N. (2022). Here comes the rain again: Productivity shocks, educational investments, and child work. *Economic Development and Cultural Change, 70*(3), 1041-1063. https://doi.org/10.1086/713937.

Paudel, J., & Ryu, H. (2018). Natural disasters and human capital: The case of Nepal's earthquake. *World Development, 111,* 1-12. https://doi.org/10.1016/j.worlddev.2018.06.019.

Phung, D. T., Nguyen, V. C., Nguyen, C. T., Nguyen, T. N., & Ta, T. K. V. (2016). Ethnic minorities and sustainable development goals: Who will be left behind? UNDP Viet Nam. Retrieved from https://www.undp.org/vietnam/publications/ethnic-minorities-and-sustainable-development-goals-who-will-be-left-behind. Accessed August 15, 2022.

Rosales-Rueda, M. (2018). The impact of early life shocks on human capital formation: Evidence from El Niño floods in Ecuador. *Journal of Health Economics, 62,* 13-44. https://doi.org/10.1016/j.jhealeco.2018.07.003.

Sacerdote, B. (2012). When the Saints Go Marching Out: Long-Term Outcomes for Student Evacuees from Hurricanes Katrina and Rita. *American Economic Journal: Applied Economics, 4*(1), 109-135. https://doi.org/10.1257/app.4.1.109.

[dataset] Sanchez, A., Woldehanna, T., Duc, L. T., Boyden, J., Penny, M., & Galab, S. (2022). *Young Lives: an International Study of Childhood Poverty: Round 5, 2016. 2nd Edition*. UK Data Service. SN: 8357, https://doi.org/10.5255/UKDA-SN-8357-2.

Shah, M., & Steinberg, B. M. (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy, 125*(2), 527-561. https://doi.org/10.1086/690828.

Singh, A. (2015). Private school effects in urban and rural India: Panel estimates at primary and secondary school ages. *Journal of Development Economics, 113,* 16-32. https://doi.org/10.1016/j.jdeveco.2014.10.004.

Takasaki, Y. (2017). Do Natural Disasters Decrease the Gender Gap in Schooling? *World Development, 94,* 75-89. https://doi.org/10.1016/j.worlddev.2016.12.041.

USAID (2017). Climate Change Risk Profile: Vietnam (Fact sheet). Washington, US. Retrieved from https://www.climatelinks.org/sites/default/files/asset/document/2017_USAID_Vietnam%20climate%20risk%20profile.pdf. Accessed August 15, 2022.

Van der Linden, W. J., & Hambleton, R. K. (1997). Item response theory: brief history, common models, and extensions. In W. J. van der Linden, & R. K. Hambleton (Eds.), *Handbook of Modern Item Response Theory* (pp. 1-28). Springer. https://doi.org/10.1007/978-1-4757-2691-6_1.

Zimmermann, L. (2020). Remember when it rained–Schooling responses to shocks in India. *World Development, 126,* 104705. https://doi.org/10.1016/j.worlddev.2019.104705.

Table 1. Definition and Summary Statistics of Variables

Variables	Definition	Obs	Mean	Std. Dev	Min	Max
Current Flood	= 1 if the household reported that floods had negatively affected household welfare during the survey year and 0 otherwise	2,858	0.018	0.134	0	1
Past Flood	= 1 if the household reported that floods had negatively affected household welfare within three years before the survey year and 0 otherwise	2,858	0.013	0.115	0	1
Children Characteristics						
IRT PPVT	Child's Peabody Picture Vocabulary Test score calculated using IRT (z score)	2,858	2.567	1.048	-4.670	8.502
Raw PPVT	Child's Peabody Picture Vocabulary Test raw score (z score)	2,858	1.218	0.468	-1.601	2.015
Enrollment	= 1 if a child is enrolled in formal school during the survey year and 0 otherwise	2,858	0.896	0.305	0	1
On Track	= 1 if a child has completed a grade appropriate for the age and 0 otherwise	2,858	0.814	0.390	0	1
Home Study Time	Hours/day spent studying outside school	2,858	2.630	1.647	0	10
School Study Time	Hours/day spent studying at school	2,858	5.324	2.265	0	12
Domestic Task Time	Hours/day spent on household chores and domestic tasks - farming, family business	2,858	1.895	1.790	0	14
Outside Work Time	Hours/day spent on paid activities outside the household	2,858	0.318	1.611	0	14
Total Study Time	Total hours/day spent studying both at school and outside school	2,858	7.954	3.160	0	15
Total Work Time	Total hours/day spent working on both domestic tasks and outside paid jobs	2,858	2.212	2.382	0	15
Male	= 1 if a child is male, and 0 if a child is female	2,858	0.512	0.500	0	1
Later-born	= 1 if a child is a later-born child, and 0 if a child is a first-born child	2,858	0.566	0.496	0	1
Aged 12	= 1 if a child is 12 years old, and 0 if a child is 15 years old	2,858	0.500	0.500	0	1
Minority	= 1 if a child belongs to an ethnic minority group, and 0 if a child belongs to the ethnic majority group (Kinh)	2,858	0.142	0.349	0	1
Household Characteristics						
Food Consumption	Monthly real food consumption (USD)	2,858	26.30	22.07	0.604	419.7
Nonfood Consumption	Monthly real nonfood consumption (USD)	2,858	23.12	37.49	0.160	1,380

Table 1. Definition and Summary Statistics of Variables (Continued)

Variables	**Definition**	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**
Access to sanitation	= 1 if a household has a safely managed sanitation service and 0 otherwise	2,858	0.805	0.396	0	1
Farmer	= 1 if agricultural income is the main household income source and 0 otherwise	2,858	0.314	0.464	0	1
Dependent	Number of dependent household members	2,858	2.204	1.077	1	9
Labor Force	Number of household members who can work	2,858	2.875	1.025	1	9
Lack of Access to Education	= 1 if a household lacks access to formal education and 0 otherwise	2,858	0.103	0.303	0	1
Access to Information	= 1 if a household has a mobile phone, television, radio, computer, or internet contract	2,858	0.078	0.269	0	1
Household Head Education						
Not Completed Secondary	= 1 if a household head has not completed secondary education	2,858	0.831	0.375	0	1
Secondary Degree	= 1 if the highest educational level of a household head is secondary	2,858	0.103	0.304	0	1
Vocational School Degree	= 1 if the highest educational level of a household head is a vocational school	2,858	0.017	0.130	0	1
University and Higher	= 1 if the highest educational level of the household head is university and higher	2,858	0.049	0.215	0	1

Table 2. Balance between affected and unaffected households

	Current Flood			Past Flood		
	Not exposure *(1)*	*Exposure* *(2)*	*Difference* *(3) = (1) - (2)*	*Not exposure* *(1)*	*Exposure* *(2)*	*Difference* *(3) = (1) - (2)*
IRT PPVT	2.569	2.421	0.148	2.568	2.489	0.079
	(1.052)	(0.841)	(0.147)	(1.051)	(0.794)	(0.171)
Child schooling						
Enrollment	0.899	0.769	0.130***	0.897	0.842	0.055
	(0.302)	(0.425)	(0.043)	(0.304)	(0.370)	(0.050)
On Track	0.816	0.692	0.123**	0.814	0.763	0.051
	(0.388)	(0.466)	(0.055)	(0.389)	(0.431)	(0.064)
Child Time Allocation						
Total Study Time	7.980	6.548	1.432***	7.968	6.934	1.034**
	(3.137)	(4.006)	(0.442)	(3.156)	(3.323)	(0.516)
Total Work Time	2.184	3.715	-1.531***	2.204	2.816	-0.612*
	(2.360)	(3.041)	(0.332)	(2.380)	(2.494)	(0.389)
Household Consumption						
Food Consumption (USD)	26.39	21.63	4.76*	26.39	19.40	7.00**
	(22.22)	(9.519)	(3.088)	(22.19)	(6.892)	(3.602)
Nonfood Consumption (USD)	23.26	15.71	7.55*	23.25	13.92	9.32*
	(37.81)	(8.649)	(5.246)	(37.72)	(8.042)	(6.122)
Number of Observations	2,806	52		2,820	38	

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicates the Robust Standard Error.
Columns 1 and 2 present the mean values of each variable for households not-exposed to floods and those exposed to floods. Column 3 reports the difference between the two means.

Table 3. Effect of Floods on PPVT Score and Potential Mechanisms

	DEPENDENT VARIABLE						
	IRT PPVT	Enrollment	On Track	Total Study Time	Total Work Time	Food Consumption	Nonfood Consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				PANEL A			
Current Flood	-0.302**	-0.136**	-0.158**	-1.418***	1.398***	-0.046	-0.034
	(0.136)	(0.055)	(0.065)	(0.529)	(0.421)	(0.066)	(0.074)
R-squared	0.049	0.214	0.175	0.061	0.199	0.041	0.101
F-statistics	6.35***	27.39***	23.58***	6.11***	26.79***	4.54***	14.74***
				PANEL B			
Current Flood	-0.307**	-0.141**	-0.162**	-1.527***	1.434***	-0.056	-0.042
	(0.136)	(0.056)	(0.066)	(0.529)	(0.429)	(0.067)	(0.073)
Past Flood	-0.062	-0.068	-0.064	-1.539*	0.516	-0.145*	-0.115
	(0.160)	(0.074)	(0.074)	(0.789)	(0.614)	(0.075)	(0.083)
R-squared	0.049	0.214	0.176	0.064	0.200	0.042	0.102
F-statistics	5.82***	25.14***	21.66***	5.72***	24.58***	4.51***	13.56***
Observations	2,858	2,858	2,858	2,858	2,858	2,858	2,858
Number of Children	1,429	1,429	1,429	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicates the Robust Standard Error.
All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table 4. Heterogeneity by Gender in the Effect of Floods on PPVT Score and Potential Mechanisms

	DEPENDENT VARIABLE				
	IRT PPVT (1)	Enrollment (2)	On Track (3)	Total Study Time (4)	Total Work Time (5)
			PANEL A		
Current Flood	-0.461**	-0.141	-0.226**	-1.961**	1.821***
	(0.218)	(0.092)	(0.104)	(0.925)	(0.671)
Current Flood*Male	0.280	0.008	0.121	0.960	-0.749
	(0.275)	(0.115)	(0.132)	(1.103)	(0.855)
R-squared	0.049	0.214	0.176	0.061	0.200
F-statistics	5.88***	25.10***	21.63***	5.61***	24.62***
			PANEL B		
Current Flood	-0.464**	-0.140	-0.225**	-1.966**	1.822***
	(0.218)	(0.087)	(0.100)	(0.862)	(0.662)
Current Flood*Male	0.257	0.012	0.126	0.883	-0.730
	(0.276)	(0.113)	(0.131)	(1.070)	(0.858)
Past Flood	0.281	-0.265**	-0.272**	-3.024***	1.101
	(0.235)	(0.118)	(0.111)	(1.139)	(0.858)
Past Flood*Male	-0.502	0.299**	0.322**	2.295	-0.927
	(0.309)	(0.147)	(0.142)	(1.517)	(1.184)
R-squared	0.050	0.217	0.179	0.066	0.201
F-statistics	5.12***	21.61***	18.74***	5.21***	21.23***
Observations	2,858	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.
All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table 5. Heterogeneity by Birth Order in the Effect of Floods on PPVT Score and Potential Mechanisms

	DEPENDENT VARIABLE				
	IRT PPVT (1)	Enrollment (2)	On Track (3)	Total Study Time (4)	Total Work Time (5)
			PANEL A		
Flood current year	-0.450*	-0.305***	-0.317***	-2.664***	2.126**
	(0.238)	(0.114)	(0.115)	(0.989)	(0.874)
Flood current year*Later-born	0.227	0.259**	0.243*	1.906*	-1.115
	(0.286)	(0.125)	(0.137)	(1.145)	(0.972)
R-squared	0.049	0.217	0.178	0.062	0.200
F-statistics	5.84***	25.36***	21.83***	5.91***	24.84***
			PANEL B		
Flood current year	-0.468*	-0.310***	-0.320***	-2.752***	2.227***
	(0.239)	(0.113)	(0.115)	(0.952)	(0.844)
Flood current year*Later-born	0.250	0.259**	0.242*	1.874*	-1.228
	(0.284)	(0.125)	(0.137)	(1.122)	(0.946)
Flood past three years	-0.271	-0.067	-0.056	-1.375*	1.557***
	(0.192)	(0.072)	(0.073)	(0.798)	(0.595)
Flood past three years*Later-born	0.371	0.000	-0.013	-0.279	-1.842
	(0.309)	(0.140)	(0.140)	(1.488)	(1.139)
R-squared	0.050	0.218	0.178	0.066	0.203
F-statistics	5.09***	21.76***	18.75***	5.28***	21.72***
Observations	2,858	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.
All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table 6. Heterogeneity by Age in the Effect of Floods on PPVT Score and Potential Mechanisms

	DEPENDENT VARIABLE				
	IRT PPVT (1)	Enrollment (2)	On Track (3)	Total Study Time (4)	Total Work Time (5)
			PANEL A		
Current Flood	-0.314**	-0.139**	-0.180***	-1.604***	1.443***
	(0.149)	(0.063)	(0.069)	(0.595)	(0.460)
Current Flood*Aged 12	0.087	0.022	0.162	1.367	-0.331
	(0.201)	(0.120)	(0.152)	(1.352)	(1.108)
R-squared	0.049	0.214	0.176	0.061	0.199
F-statistics	5.99***	25.10***	21.63***	5.62***	24.55***
			PANEL B		
Current Flood	-0.291*	-0.134**	-0.174**	-1.541**	1.335***
	(0.152)	(0.065)	(0.072)	(0.610)	(0.491)
Current Flood*Aged 12	-0.097	-0.050	0.099	0.159	0.670
	(0.337)	(0.169)	(0.184)	(1.786)	(1.455)
Past Flood	-0.147	-0.087	-0.062	-1.604	0.931
	(0.232)	(0.101)	(0.100)	(1.135)	(0.715)
Past Flood*Aged 12	0.220	0.032	0.054	0.309	-0.959
	(0.356)	(0.146)	(0.158)	(1.512)	(1.208)
R-squared	0.049	0.214	0.176	0.064	0.200
F-statistics	5.16***	21.54***	18.56***	4.90***	21.11***
Observations	2,858	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.
All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table 7. Heterogeneity by Ethnicity in the Effect of Floods on PPVT Score and its Potential Mechanisms

	DEPENDENT VARIABLE						
	IRT PPVT	Enrollment	On Track	Total Study Time	Total Work Time	Food Consumption	Nonfood Consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				PANEL A			
Current Flood	-0.239*	-0.125**	-0.152**	-1.391***	1.234***	0.011	-0.007
	(0.140)	(0.054)	(0.065)	(0.533)	(0.430)	(0.057)	(0.077)
Current Flood*Minority	-0.972***	-0.169	-0.096	-0.412	2.522*	-0.887**	-0.412***
	(0.216)	(0.329)	(0.323)	(2.806)	(1.428)	(0.369)	(0.153)
R-squared	0.050	0.214	0.175	0.061	0.201	0.045	0.102
F-statistics	8.97***	25.10***	21.60***	5.60***	25.07***	4.76***	13.61***
				PANEL B			
Current Flood	-0.236*	-0.134**	-0.160**	-1.514***	1.263***	-0.002	-0.014
	(0.138)	(0.055)	(0.066)	(0.535)	(0.438)	(0.059)	(0.076)
Current Flood*Minority	-0.974***	-0.162	-0.090	-0.302	2.493*	-0.876**	-0.405***
	(0.215)	(0.329)	(0.324)	(2.812)	(1.432)	(0.369)	(0.153)
Past Flood	0.044	-0.112	-0.111	-1.632**	0.382	-0.173**	-0.095
	(0.161)	(0.079)	(0.078)	(0.808)	(0.652)	(0.085)	(0.085)
Past Flood*Minority	-0.736	0.336**	0.348**	0.698	0.876	0.246**	-0.127
	(0.508)	(0.167)	(0.174)	(2.838)	(1.812)	(0.113)	(0.290)
R-squared	0.051	0.217	0.178	0.064	0.201	0.047	0.103
F-statistics	7.86***	21.78***	18.74***	4.91***	21.49***	4.57***	11.70***
Observations	2,858	2,858	2,858	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.
All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

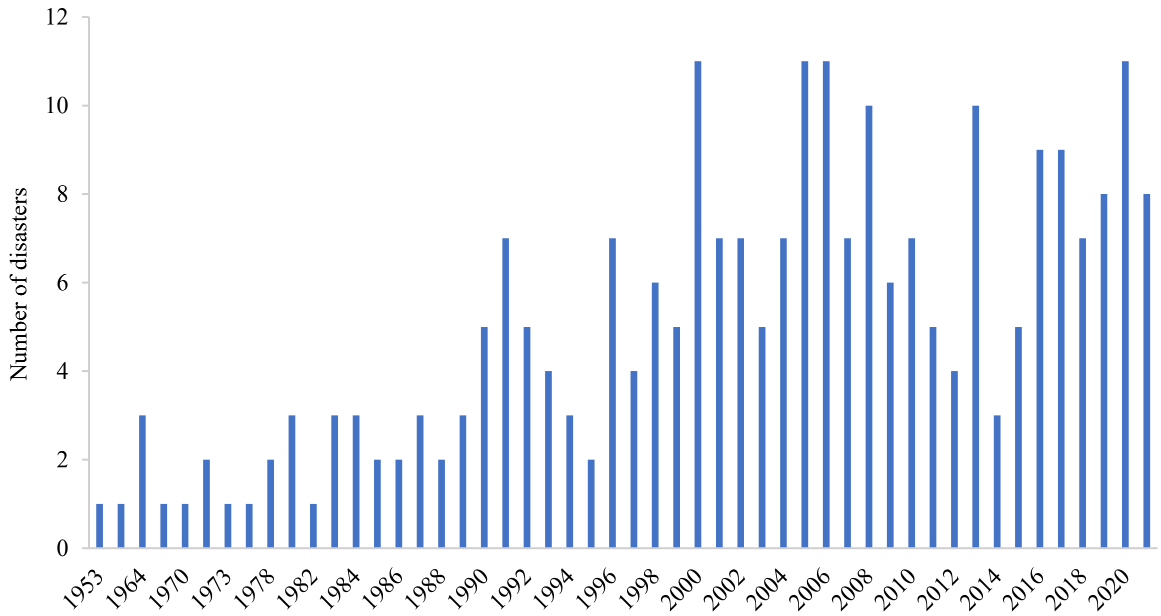

Figure 1. Historical record (1953–2021) of the total number of natural disasters per year in Vietnam

Source: Data is retrieved from www.public.emdat.be. Accessed August 10, 2022

Figure 2. Young Lives study sites in Vietnam

NOTES: Red points represent the study sites of the Young Lives study in Vietnam.

Source: Le and Nguyen (2014)

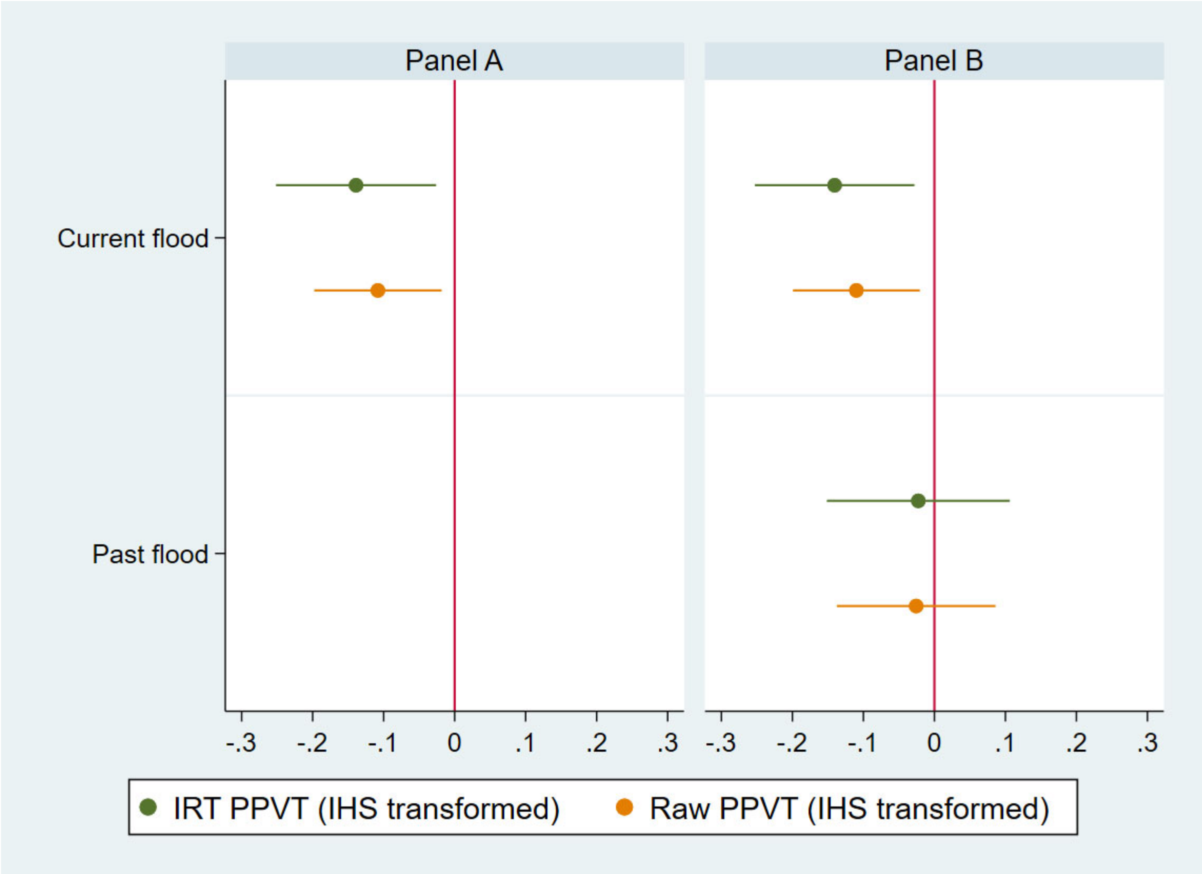

Figure 3. Comparison of the estimated coefficients of flood effects on PPVT score as calculated by IRT method and the raw aggregates of correct answers

NOTES:

(1) Panel A presents the model considering only the effect of floods in the current year. Panel B presents the model capturing the effects of both past and contemporaneous rainfall shocks.

(2) Because IRT and the raw scores can take zero values, we transform them using the inverse hyperbolic sine (IHS) to facilitate the comparison. Due to this transformation, the estimates of β_1 and β_2 can be interpreted as the percentage change in PPVT scores caused by exposure to current and past floods, respectively.

(3) Both IRT scores and raw scores are normalized by cohort to have a mean of 0 during the first period in which the test is administered (Round 2).

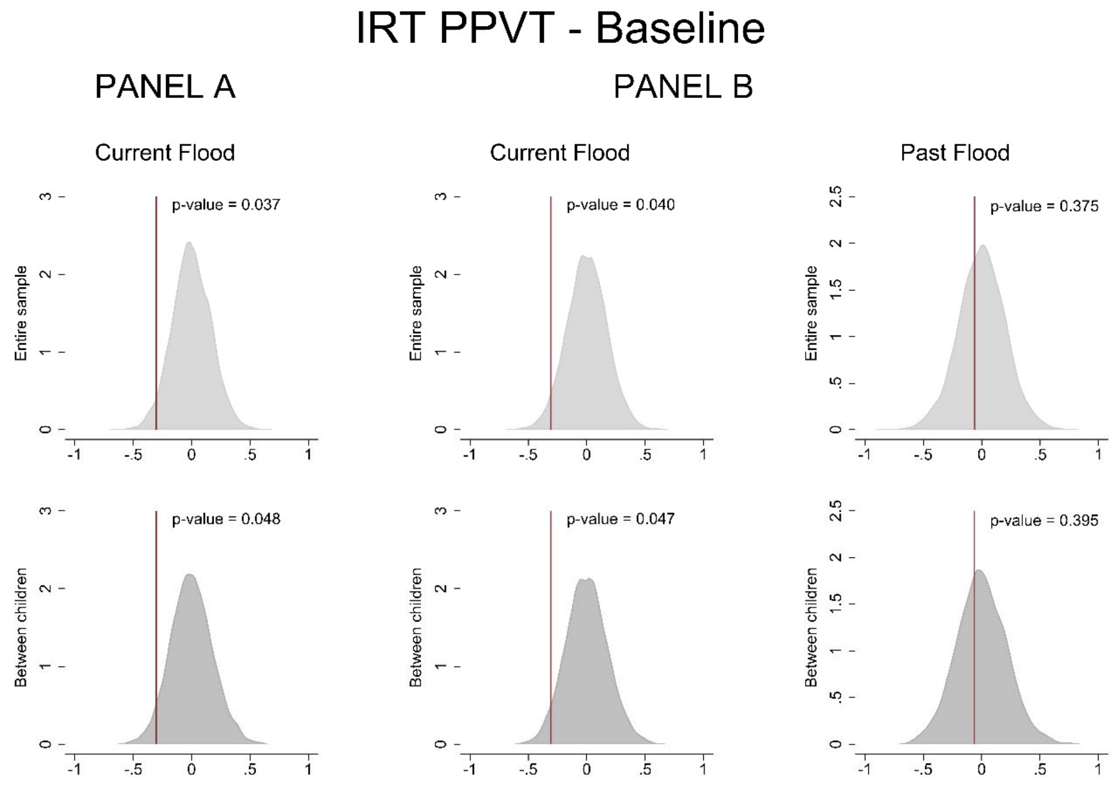

Figure 4. Randomization Inference Distributions – IRT PPVT: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

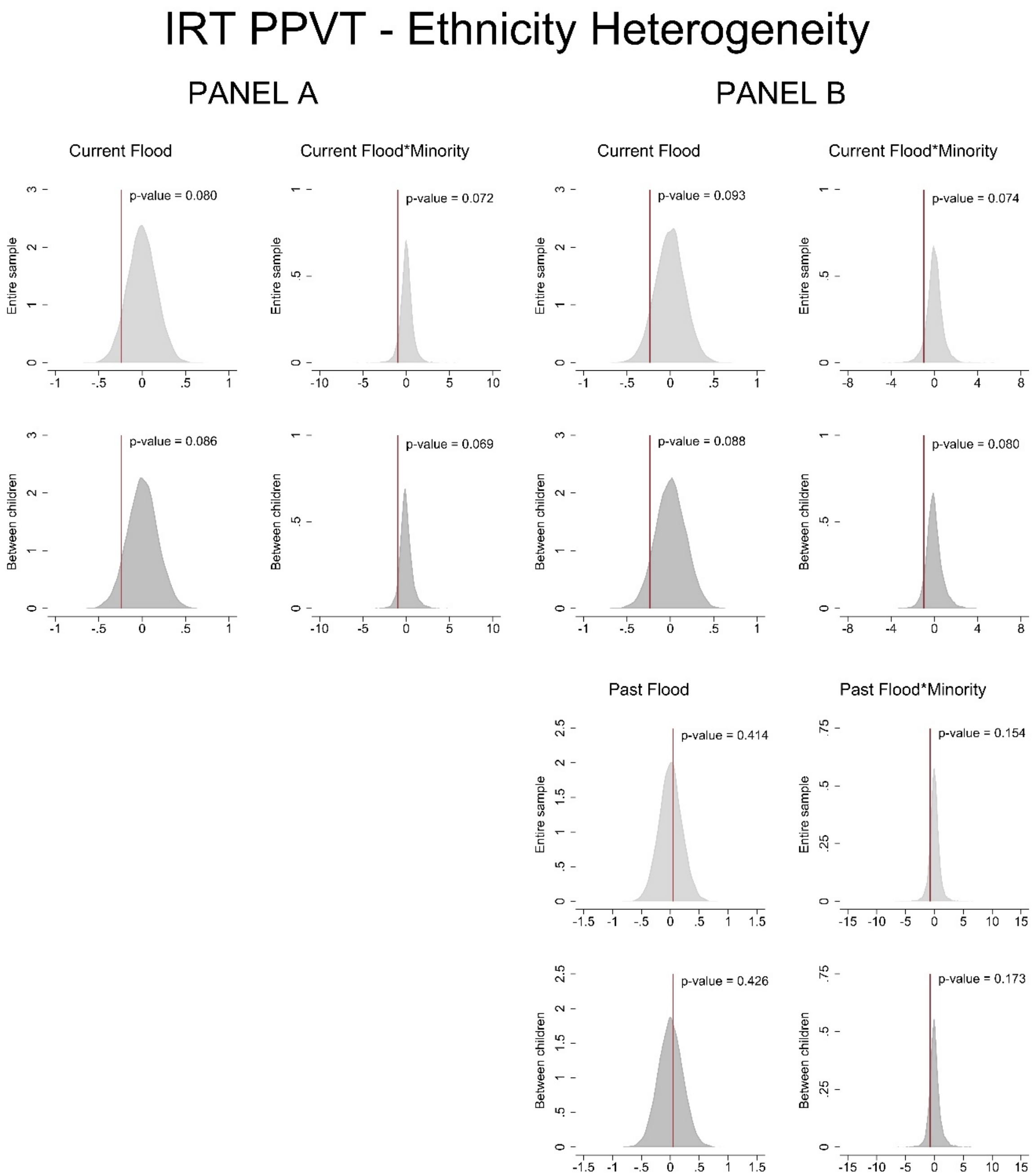

Figure 5. Randomization Inference Distributions – IRT PPVT: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

Appendix A. Literature overview of the heterogeneous impact of shocks on outcomes of interest

Paper	Disaster	Outcomes			
		Test Score	**Education Attainment**	**Child Labor**	**Consumption**
Adhvaryu et al. (2018)	Rainfall	age	age		
Aguilar and Vicarelli (2022)	Rainfall	age			
Baez and Santos (2007)	Hurricane		location	location	
Björkman-Nyqvist (2013)	Rainfall	gender	gender, age		
Carrillo (2020)	Rainfall		location, age		
Caruso (2017)	Multiple types		gender, age		
Caruso and Miller (2015)	Earthquake		gender, age		
Colmer (2021)	Rainfall		gender, age	gender, age	
Dumas (2020)	Rainfall			gender, age	
Feeny et al. (2021)	Rainfall		gender		
Gitter and Barham (2007)	Hurricane		gender, birth order, age		
Groppo and Kraehnert (2017)	Severe winter		production activity, gender, age		production activity
de Janvry et al. (2006)	Drought, other natural disasters		production activity, gender, age	production activity, age	
Zimmermann (2020)	Rainfall		gender, age	gender, age	
Leight et al. (2015)	Rainfall	age			
Mottaleb et al. (2015)	Cyclone				production activity
Nordman et al. (2022)	Rainfall			caste, gender	caste
Paudel and Ryu (2018)	Earthquake		caste, gender, age		
Rosales-Rueda (2018)	Flood	location, age			location
Shah and Steinberg (2017)	Rainfall	age	age	age	
Takasaki (2017)	Cyclone		gender, birth order, age		
de Vreyer et al. (2012)	Locust invasion		gender, age		

Note: Shock indicates the type of shock a paper uses to study the impact on the outcomes of interest. Test score represents cognitive ability and academic performance. Education attainment represents school enrollment, years of schooling, and study hours both at school and outside school. Child labor represents children's work participation and work hours. Consumption represents household consumption.

Age represents the heterogeneity by ages of shock experience. Gender represents the heterogeneity between boys and girls. Production activity represents the heterogeneous between farm and nonfarm households. Caste represents the heterogeneity by caste groups. Birth order represents the heterogeneous by birth order. Finally, location represents the heterogeneity between rural and urban areas.

Appendix B. Additional Results for the Effect of Floods on Time Allocation across Specific Study and Work Activities

Table B1. Effect of Floods on Time Allocation across Specific Study and Work Activities

	DEPENDENT VARIABLE			
	Home Study Time (1)	School Study Time (2)	Domestic Task Time (3)	Outside Work Time (4)
	PANEL A			
Current Flood	0.038	-1.456***	0.654**	0.743*
	(0.239)	(0.419)	(0.273)	(0.415)
R-squared	0.015	0.071	0.102	0.107
F-statistics	2.32***	7.28***	13.92***	9.59***
	PANEL B			
Current Flood	0.013	-1.539***	0.717**	0.717*
	(0.237)	(0.421)	(0.282)	(0.419)
Past Flood	-0.363	-1.176*	0.891*	-0.375
	(0.367)	(0.619)	(0.466)	(0.435)
R-squared	0.016	0.075	0.105	0.107
F-statistics	2.20***	6.80***	12.89***	8.80***
Observations	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.

All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table B2. Heterogeneity by Gender in the Effect of Floods on Time Allocation by Specific Study and Work Activities

	DEPENDENT VARIABLE			
	Home Study Time (1)	School Study Time (2)	Domestic Task Time (3)	Outside Work Time (4)
	PANEL A			
Current Flood	-0.068	-1.893***	0.962**	0.859
	(0.355)	(0.712)	(0.410)	(0.624)
Current Flood*Male	0.188	0.772	-0.544	-0.205
	(0.477)	(0.867)	(0.541)	(0.839)
R-squared	0.016	0.072	0.102	0.107
F-statistics	2.13**	6.68***	12.86***	8.80***
	PANEL B			
Current Flood	-0.061	-1.905***	0.968**	0.854
	(0.305)	(0.696)	(0.391)	(0.625)
Current Flood*Male	0.231	0.652	-0.473	-0.257
	(0.449)	(0.867)	(0.542)	(0.848)
Past Flood	-1.832***	-1.193	1.279	-0.178
	(0.482)	(0.969)	(0.845)	(0.343)
Past Flood*Male	2.230***	0.064	-0.614	-0.313
	(0.622)	(1.255)	(1.014)	(0.725)
R-squared	0.023	0.075	0.106	0.108
F-statistics	3.00***	5.84***	11.28***	7.56***
Observations	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.

All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table B3. Heterogeneity by Birth Order in Effect of Floods on Time Allocation by Specific Study and Work Activities

	DEPENDENT VARIABLE			
	Home Study Time (1)	School Study Time (2)	Domestic Task Time (3)	Outside Work Time (4)
	PANEL A			
Current Flood	0.184	-2.847***	0.446	1.680*
	(0.414)	(0.669)	(0.593)	(0.912)
Current Flood*Later-born	-0.223	2.129***	0.318	-1.433
	(0.500)	(0.823)	(0.648)	(0.990)
R-squared	0.016	0.075	0.102	0.110
F-statistics	2.13**	7.79***	13.22***	8.84***
	PANEL B			
Current Flood	0.167	-2.919***	0.546	1.681*
	(0.394)	(0.660)	(0.547)	(0.918)
Current Flood*Later-born	-0.237	2.111**	0.253	-1.481
	(0.490)	(0.821)	(0.617)	(0.997)
Past Flood	-0.268	-1.108*	1.543***	0.013
	(0.502)	(0.573)	(0.368)	(0.361)
Past Flood*Later-born	-0.170	-0.109	-1.148	-0.694
	(0.720)	(1.150)	(0.835)	(0.811)
R-squared	0.016	0.079	0.107	0.111
F-statistics	1.89**	6.88***	12.53***	7.60***
Observations	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.

All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table B4. Heterogeneity by Age in the Effect of Floods on Time Allocation by Specific Study and Work Activities

	DEPENDENT VARIABLE			
	Home Study Time (1)	School Study Time (2)	Domestic Task Time (3)	Outside Work Time (4)
	PANEL A			
Current Flood	-0.023	-1.580***	0.610**	0.833*
	(0.248)	(0.469)	(0.279)	(0.471)
Current Flood*Aged 12	0.453	0.914	0.328	-0.659
	(0.546)	(1.067)	(0.760)	(0.937)
R-squared	0.016	0.072	0.102	0.107
F-statistics	2.19**	6.67***	12.76***	8.80***
	PANEL B			
Current Flood	-0.123	-1.418***	0.442	0.893*
	(0.246)	(0.495)	(0.291)	(0.506)
Current Flood*Aged 12	0.951	-0.792	2.036**	-1.367
	(0.681)	(1.490)	(1.027)	(1.161)
Past Flood	0.134	-1.738**	1.703***	-0.772***
	(0.472)	(0.868)	(0.650)	(0.221)
Past Flood*Aged 12	-1.060	1.369	-1.437*	0.478
	(0.747)	(1.175)	(0.833)	(0.935)
R-squared	0.018	0.076	0.108	0.109
F-statistics	2.12***	5.86***	11.11***	7.56***
Observations	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.

All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Table B5. Heterogeneity by Ethnicity in the Effect of Floods on Time Allocation by Specific Study and Work Activities

	DEPENDENT VARIABLE			
	Home Study Time (1)	School Study Time (2)	Domestic Task Time (3)	Outside Work Time (4)
	PANEL A			
Current Flood	0.066	-1.458***	0.442*	0.793*
	(0.249)	(0.416)	(0.255)	(0.441)
Current Flood*Minority	-0.436	0.024	3.286***	-0.765
	(0.780)	(2.456)	(1.067)	(0.590)
R-squared	0.016	0.071	0.106	0.107
F-statistics	2.13**	6.71***	14.02***	8.79***
	PANEL B			
Current Flood	0.038	-1.552***	0.480*	0.783*
	(0.249)	(0.419)	(0.259)	(0.447)
Current Flood*Minority	-0.411	0.108	3.244***	-0.751
	(0.780)	(2.461)	(1.071)	(0.593)
Past Flood	-0.376	-1.256**	0.522	-0.140
	(0.421)	(0.558)	(0.471)	(0.445)
Past Flood*Minority	0.112	0.585	2.587**	-1.711
	(0.536)	(2.930)	(1.303)	(1.381)
R-squared	0.016	0.075	0.112	0.109
F-statistics	1.91**	5.97***	12.34***	7.60***
Observations	2,858	2,858	2,858	2,858
Number of children	1,429	1,429	1,429	1,429

Notes: ***, ** and * indicate 1%, 5% and 10% significant levels. The values in parentheses indicate the Robust Standard Error.
All specifications control for the household head's education, number of working-aged members, number of dependents, whether agricultural income is the most important income source, whether the household lacks access to education, whether the household has sanitary latrines, and whether the household has access to information.

Appendix C. Additional Results of Placebo Tests for IRT PPVT

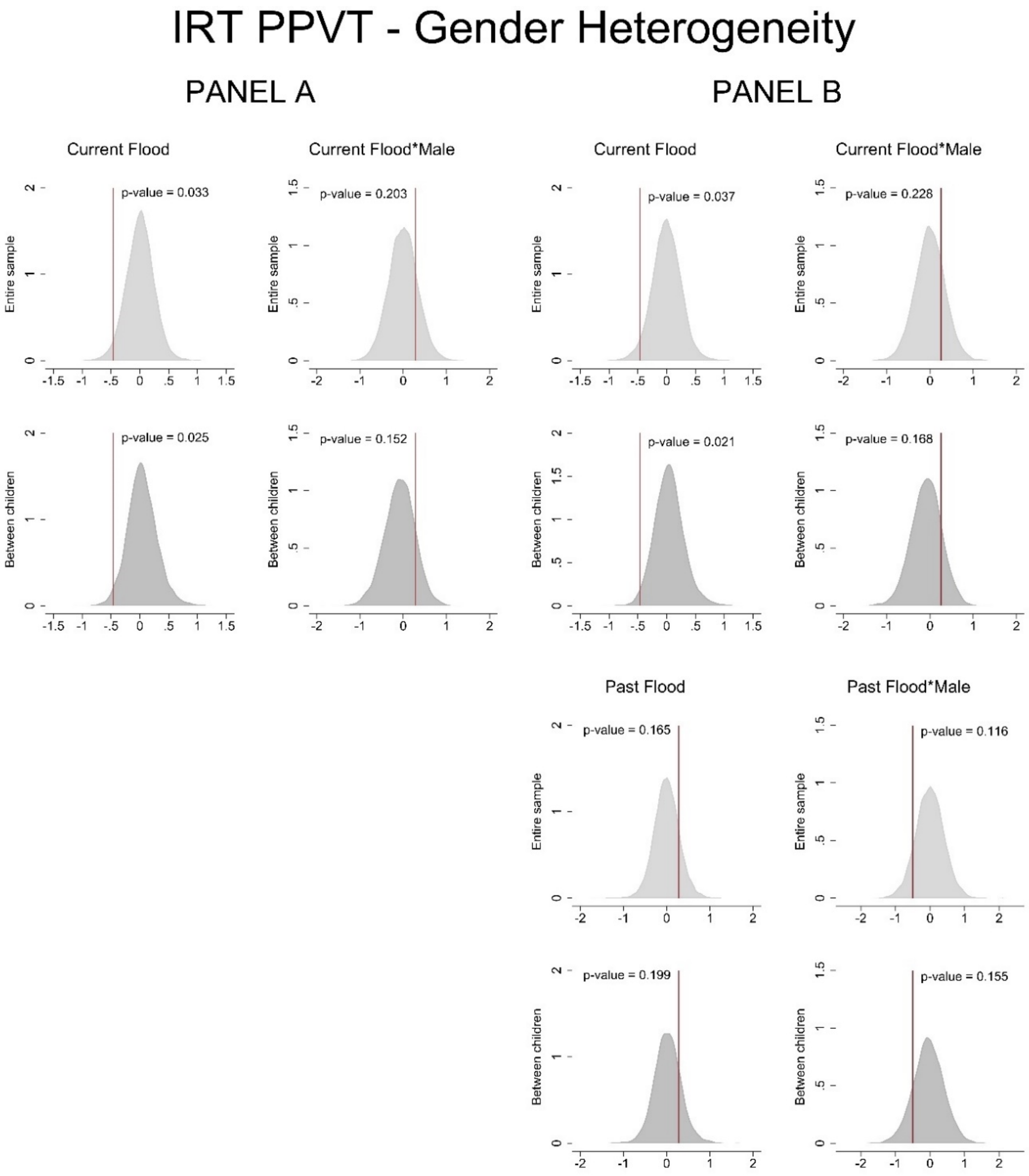

Figure C1. Randomization Inference Distributions – IRT PPVT: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

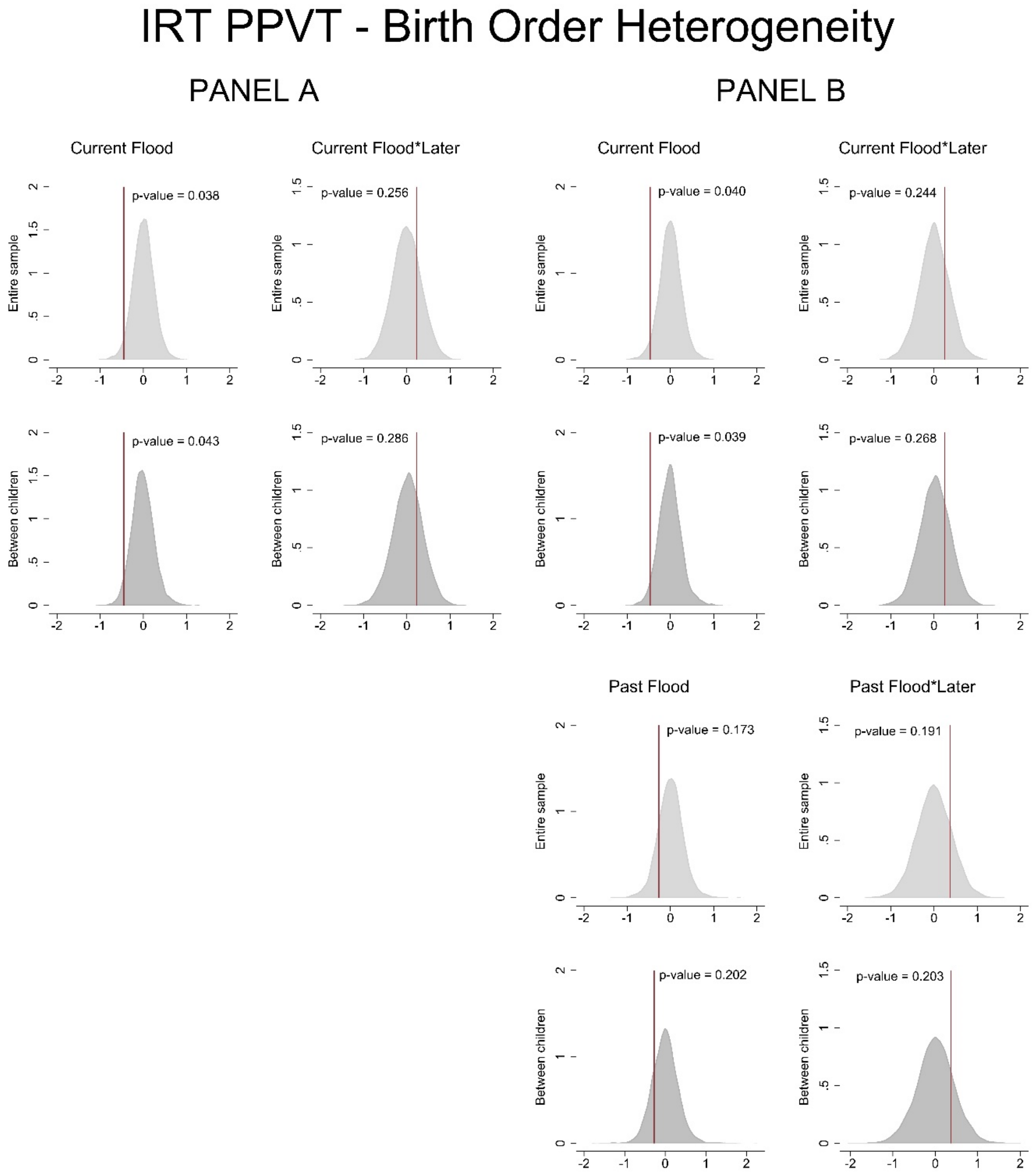

Figure C2. Randomization Inference Distributions – IRT PPVT: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

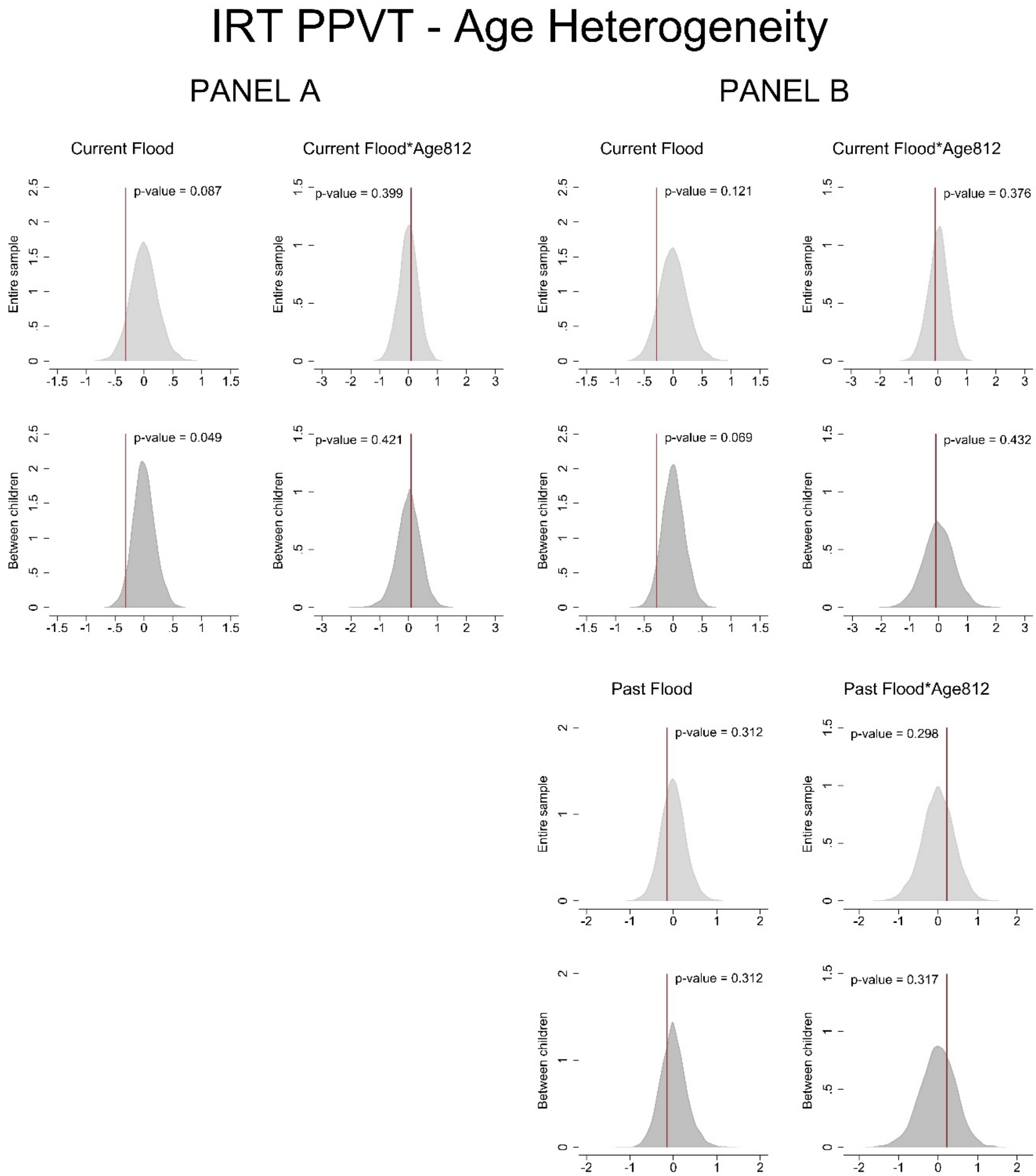

Figure C3. Randomization Inference Distributions – IRT PPVT: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

Appendix D. Results of Placebo Tests for Other Outcomes

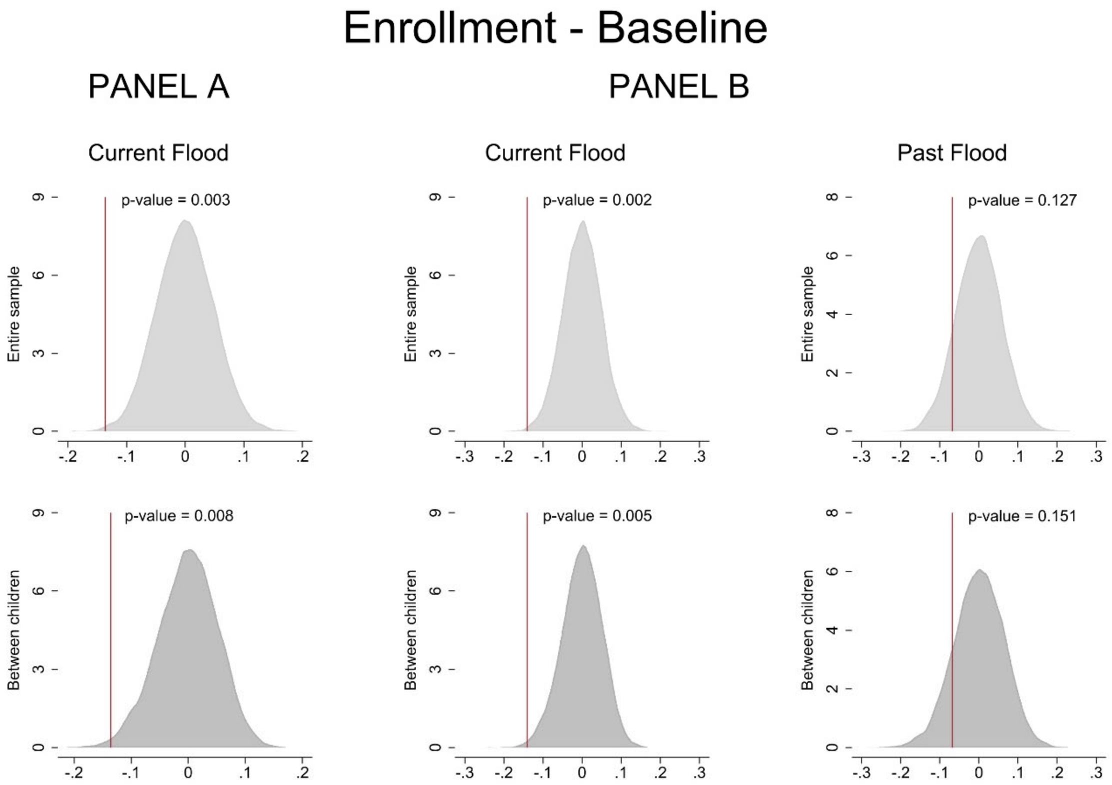

Figure D1.1. Randomization Inference Distributions – Enrollment: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

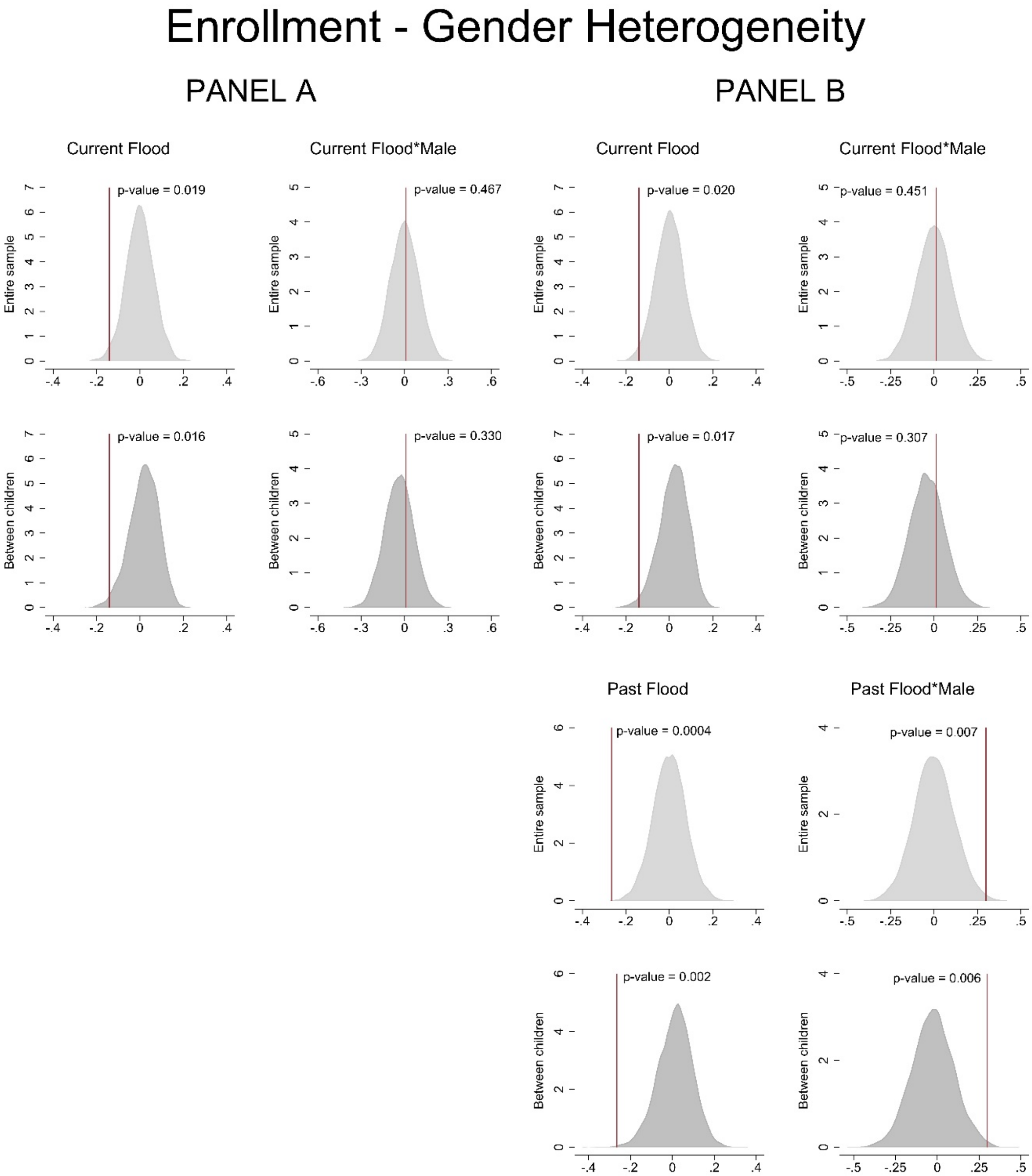

Figure D1.2. Randomization Inference Distributions – Enrollment: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

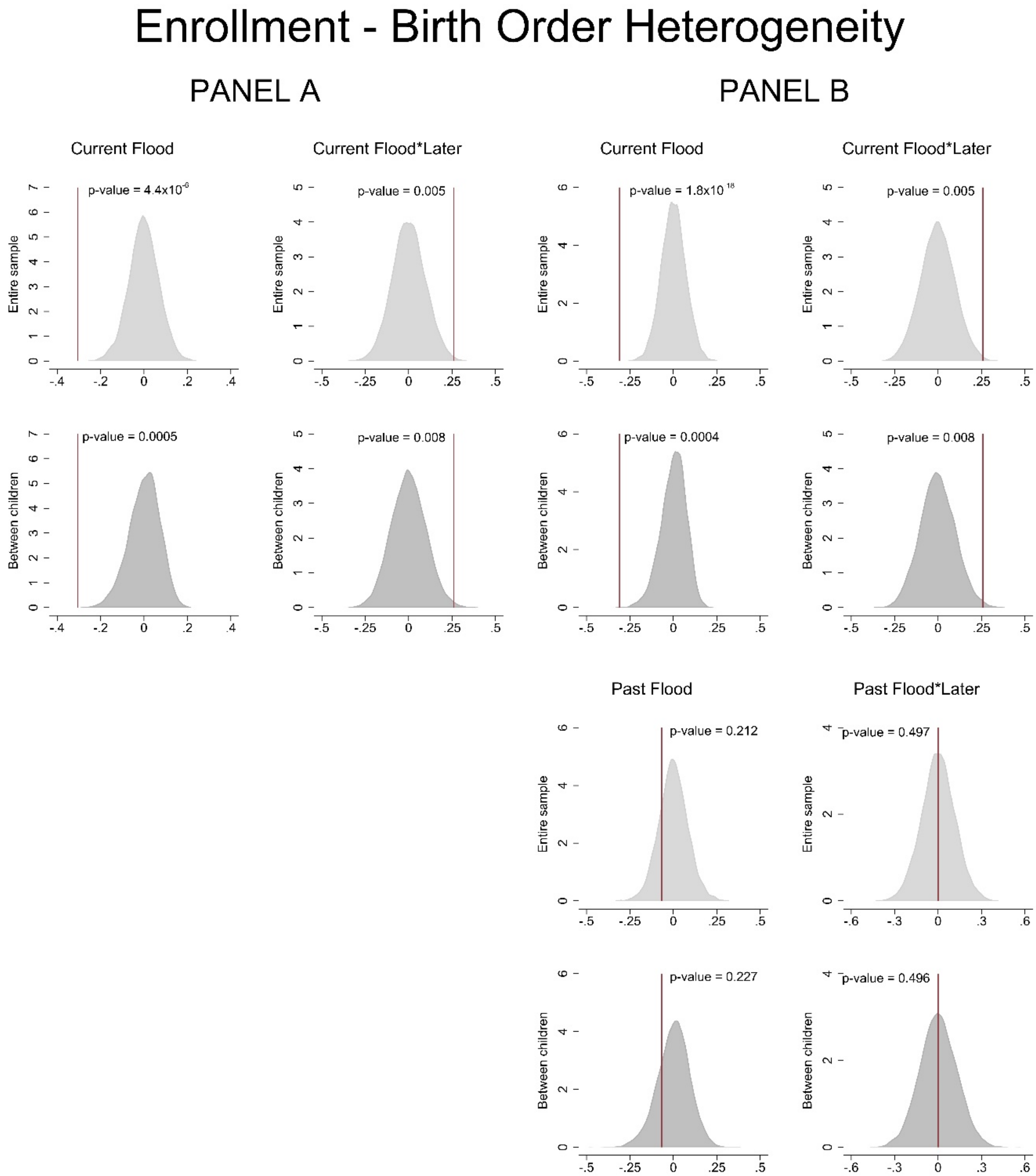

Figure D1.3. Randomization Inference Distributions – Enrollment: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

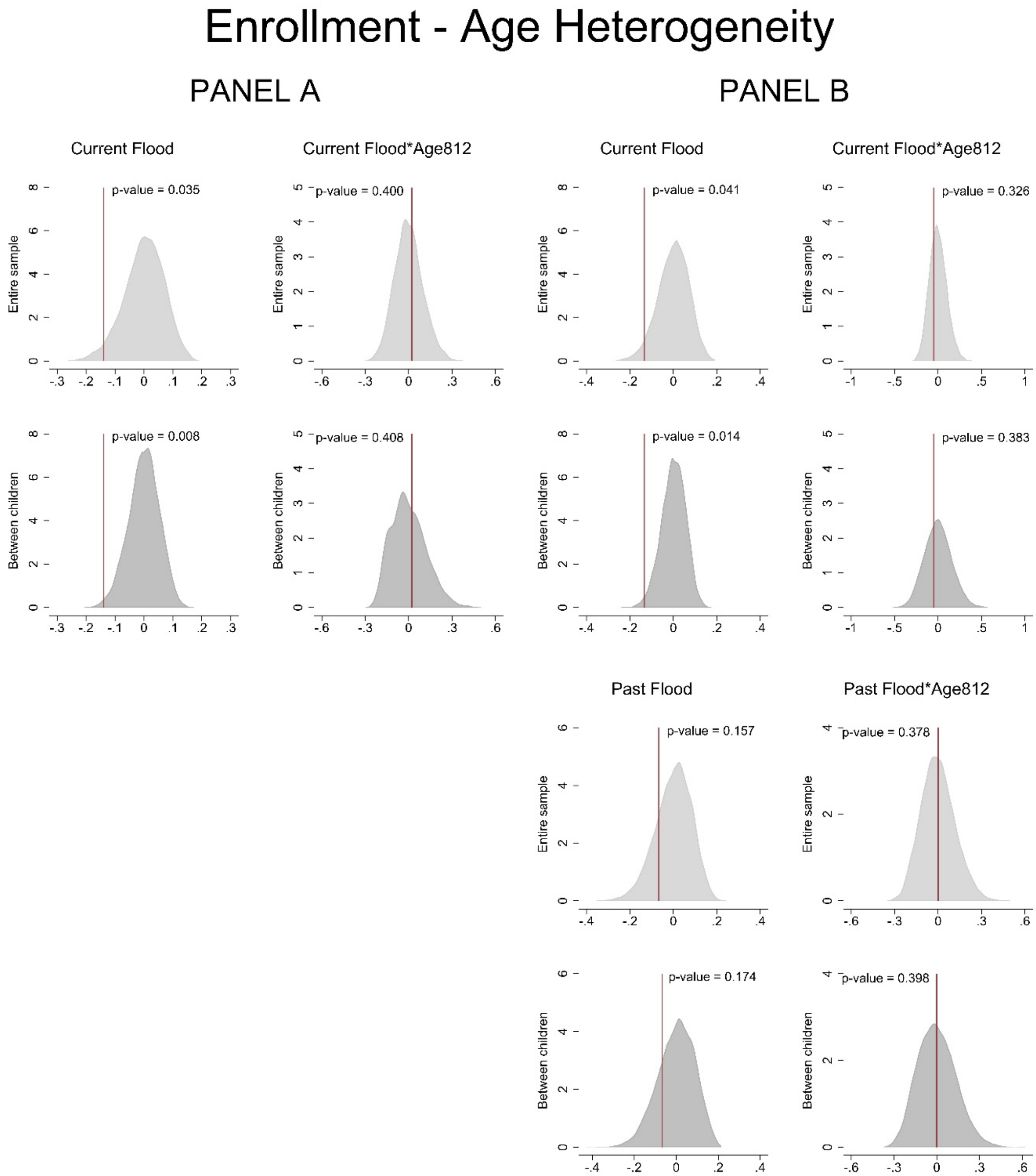

Figure D1.4. Randomization Inference Distributions – Enrollment: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

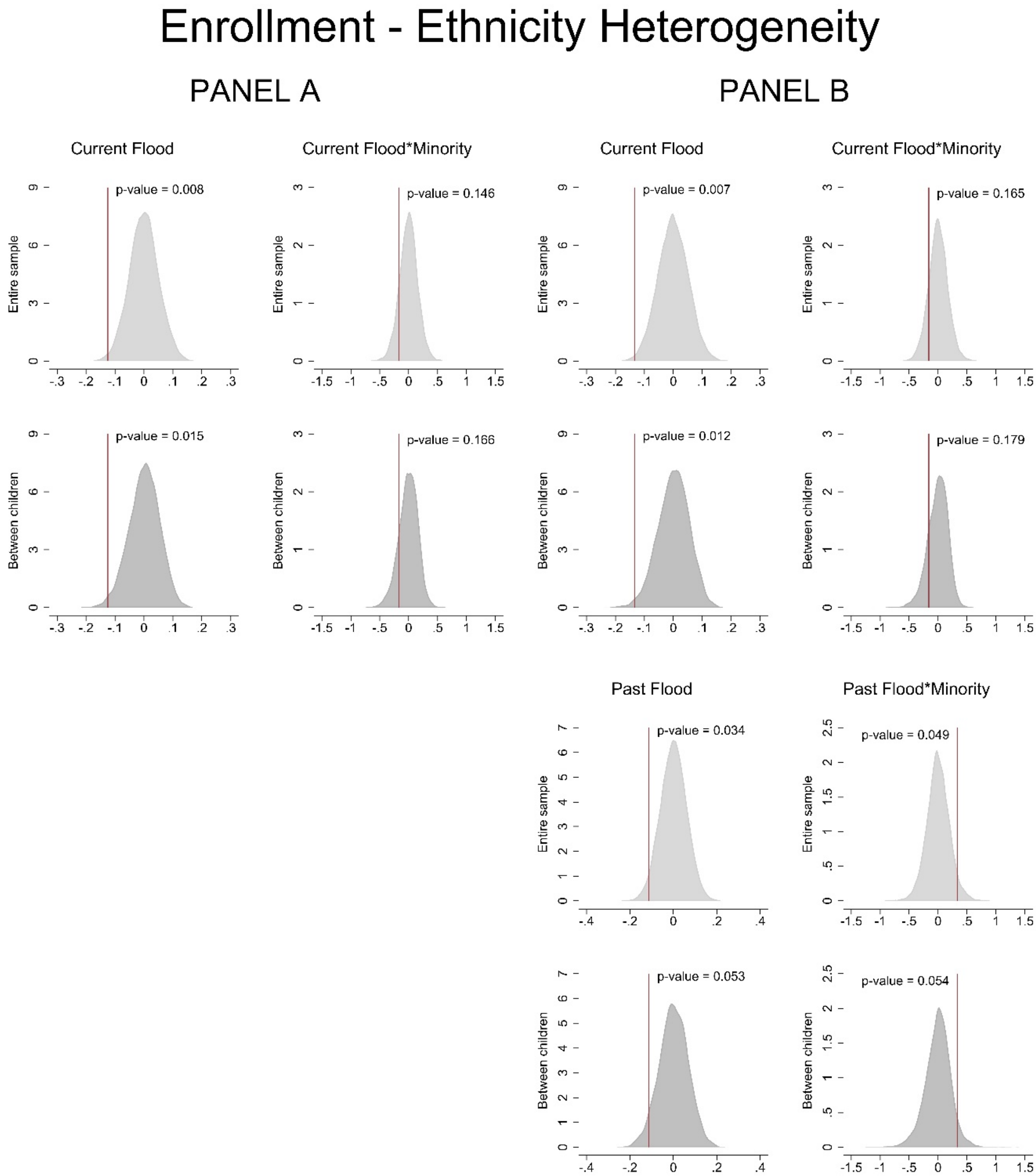

Figure D1.5. Randomization Inference Distributions – Enrollment: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

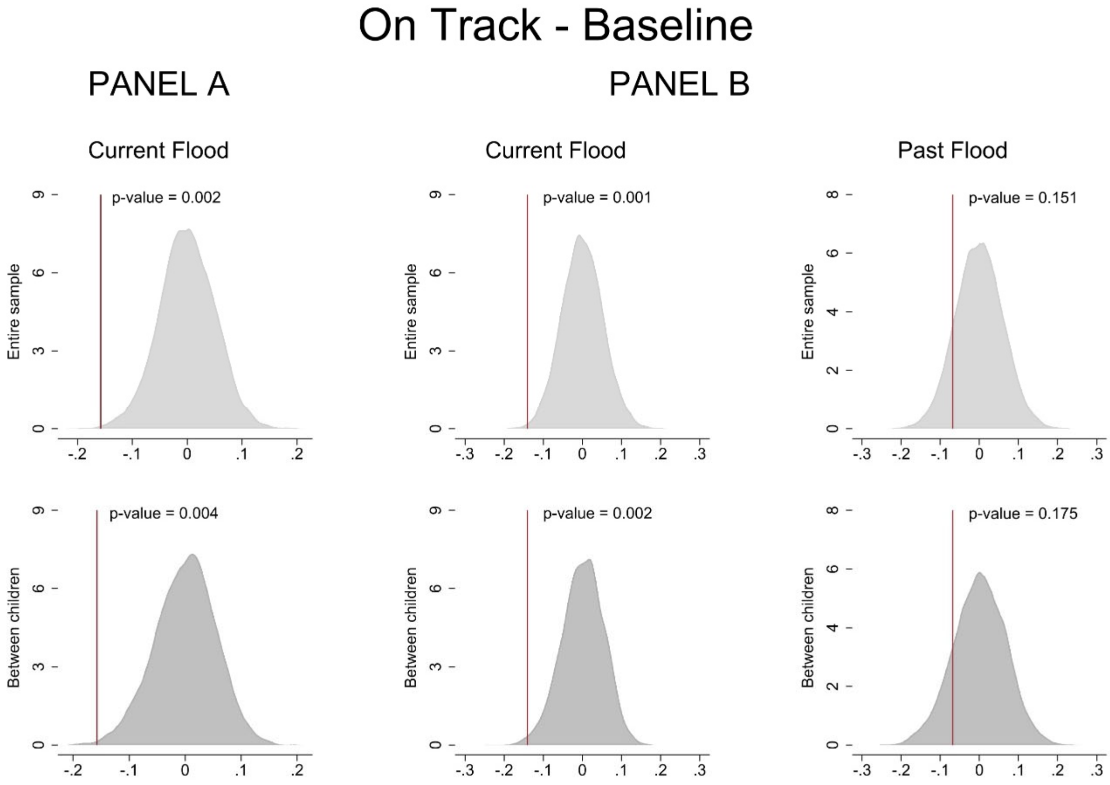

Figure D2.1. Randomization Inference Distributions – On Track: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

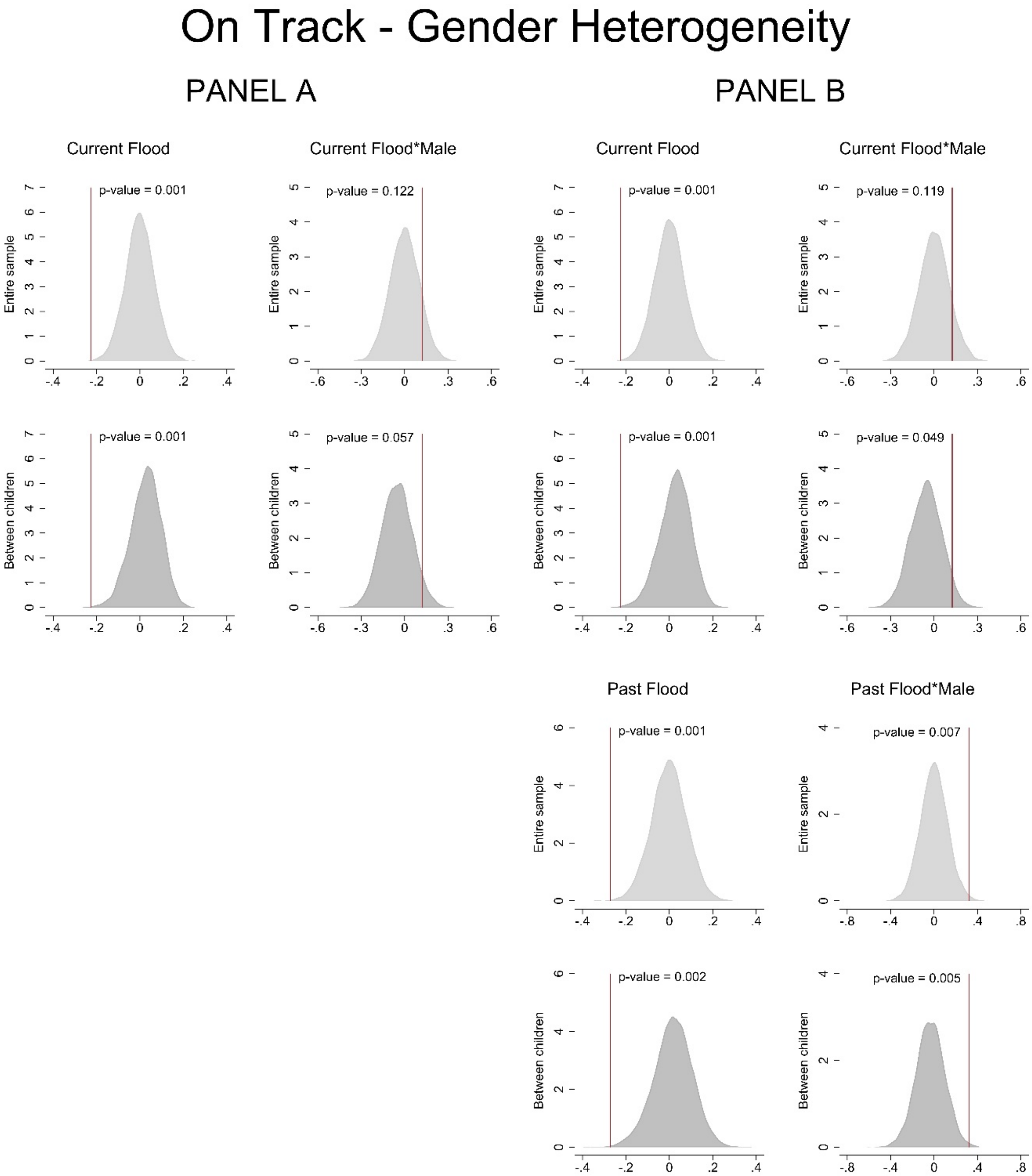

Figure D2.2. Randomization Inference Distributions – On Track: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

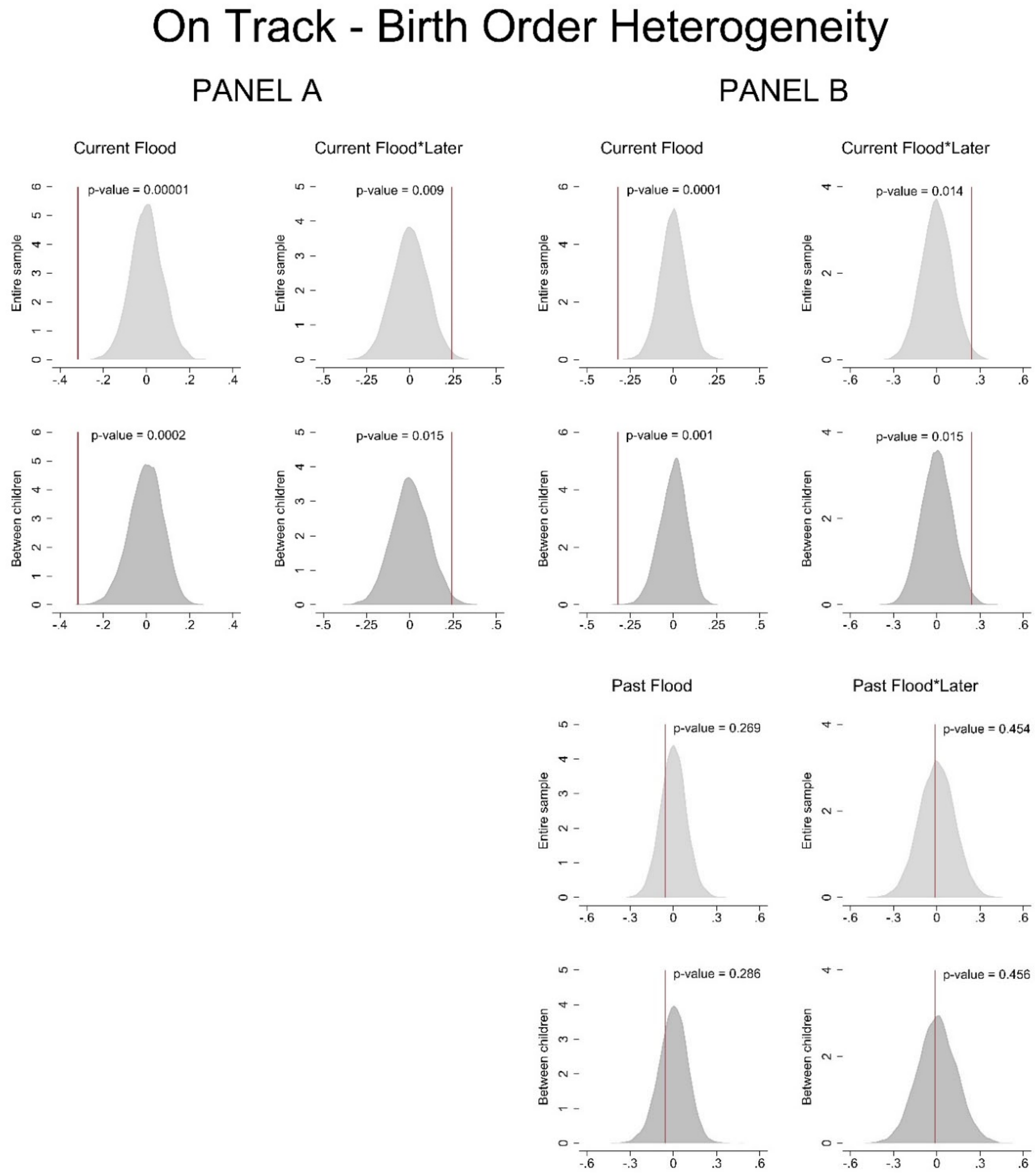

Figure D2.3. Randomization Inference Distributions – On Track: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

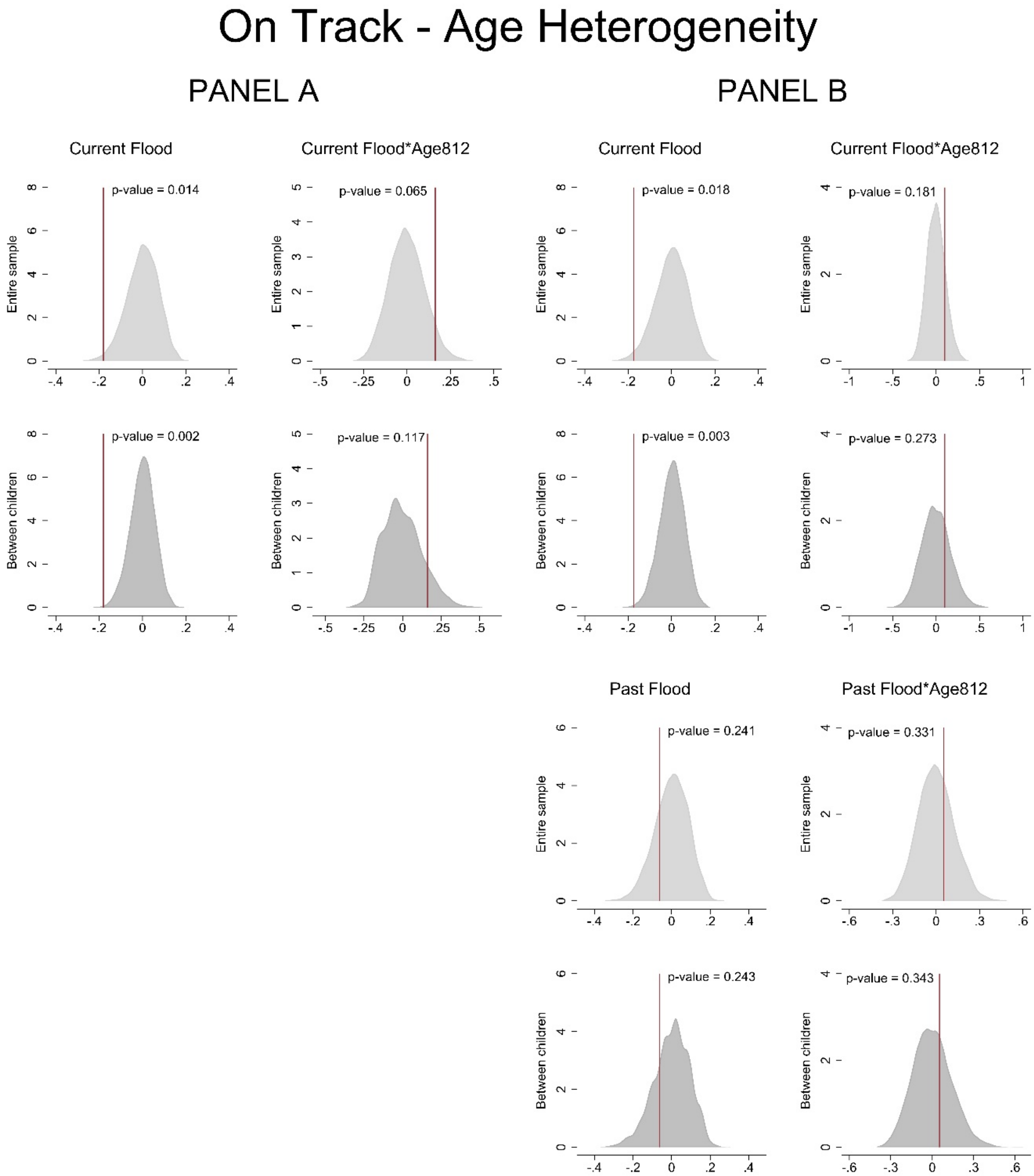

Figure D2.4. Randomization Inference Distributions – On Track: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

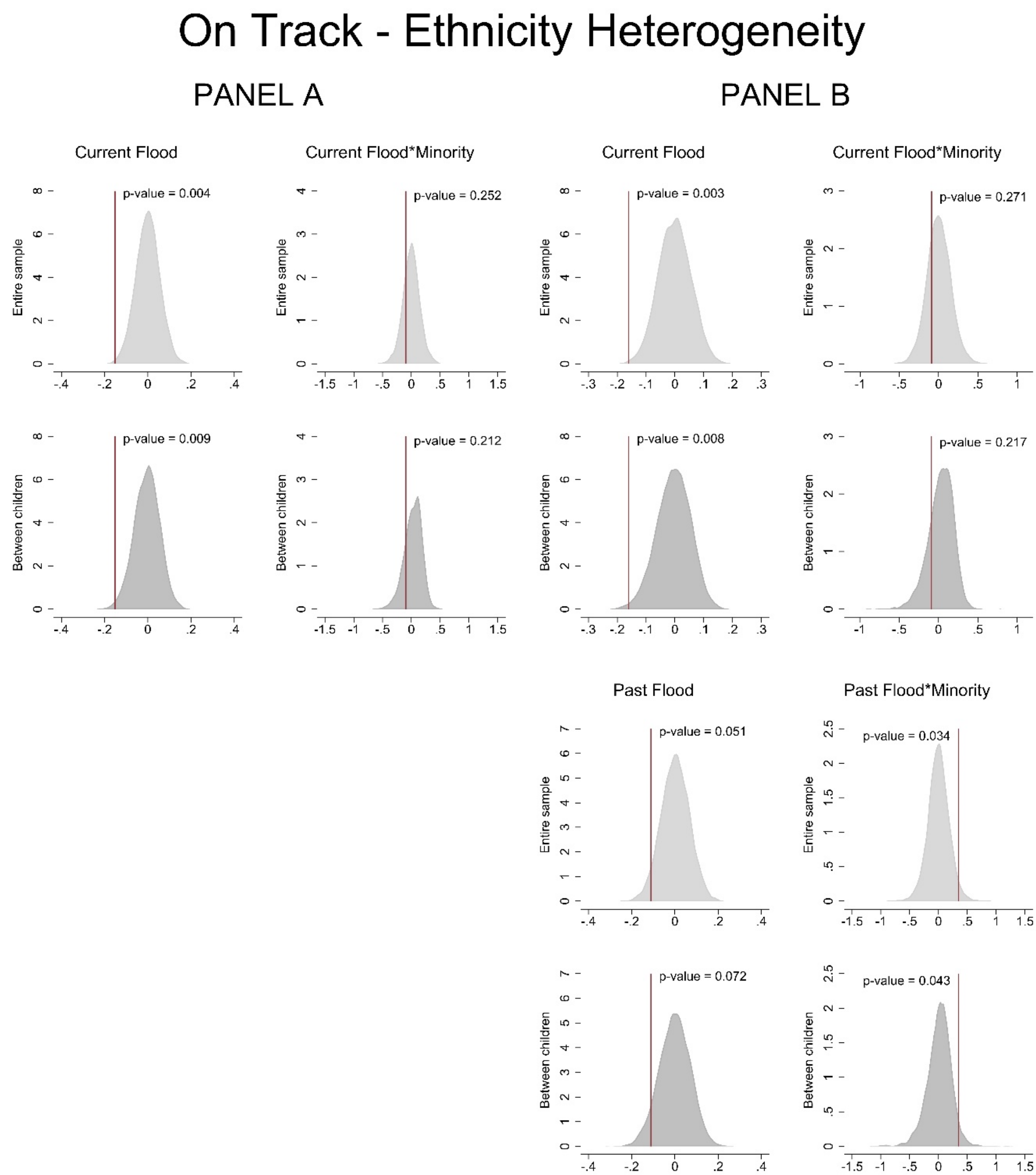

Figure D2.5. Randomization Inference Distributions – On Track: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

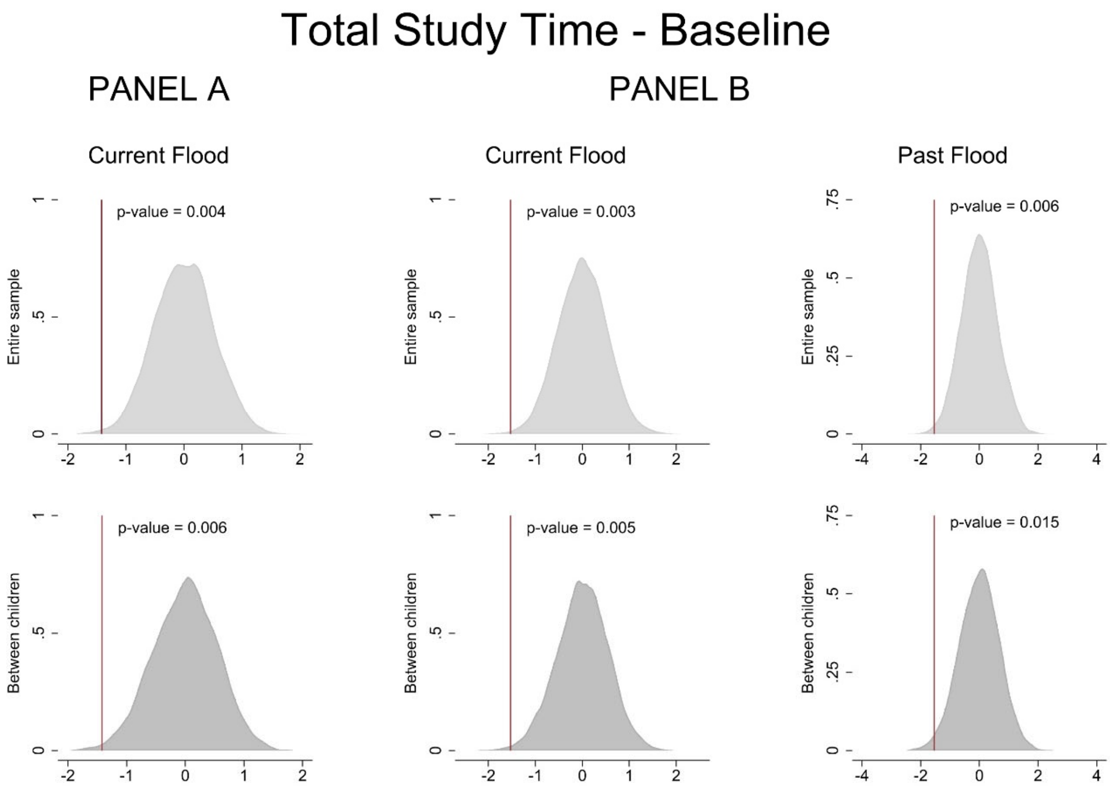

Figure D3.1. Randomization Inference Distributions – Total Study Time: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

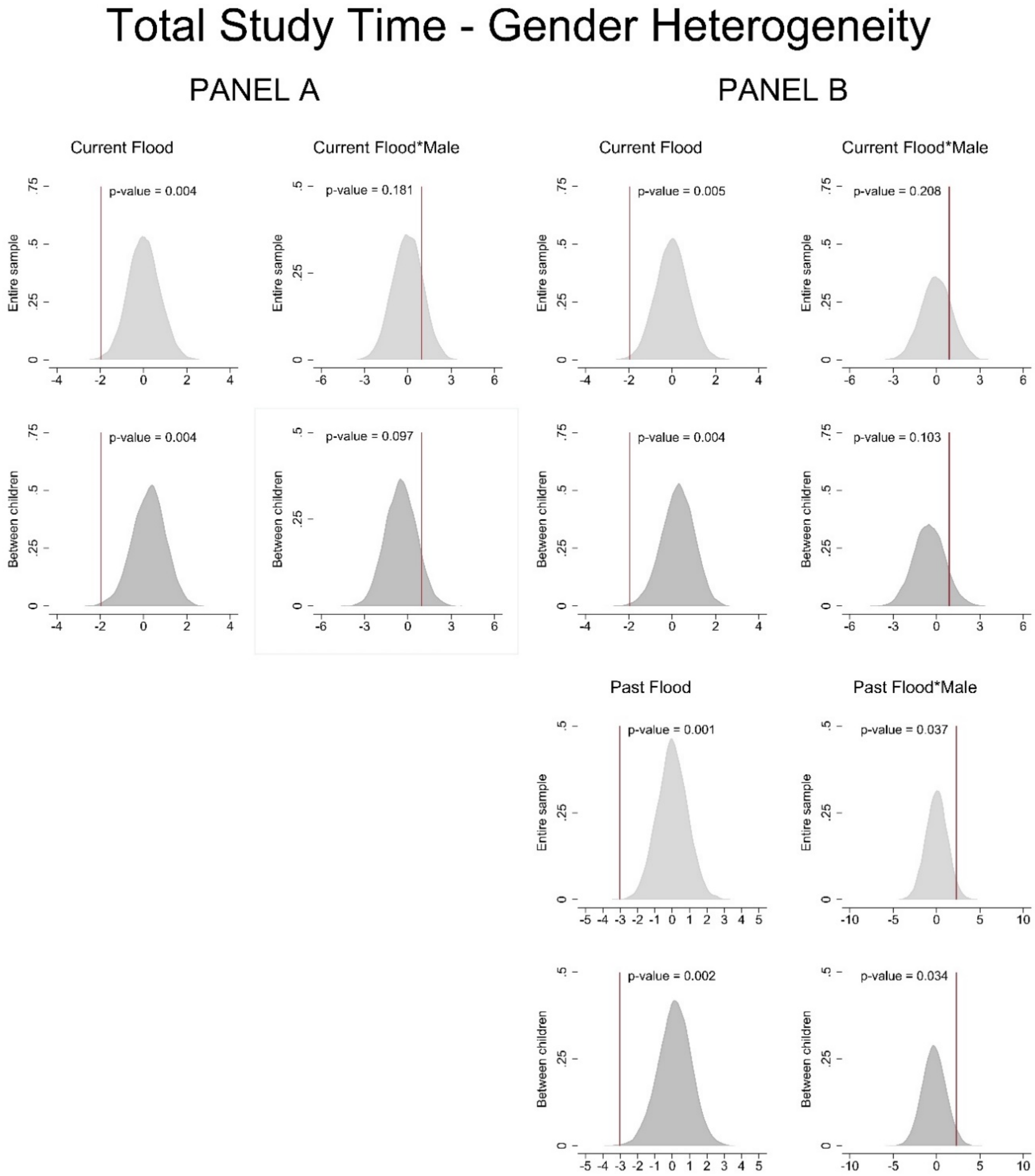

Figure D3.2. Randomization Inference Distributions – Total Study Time: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

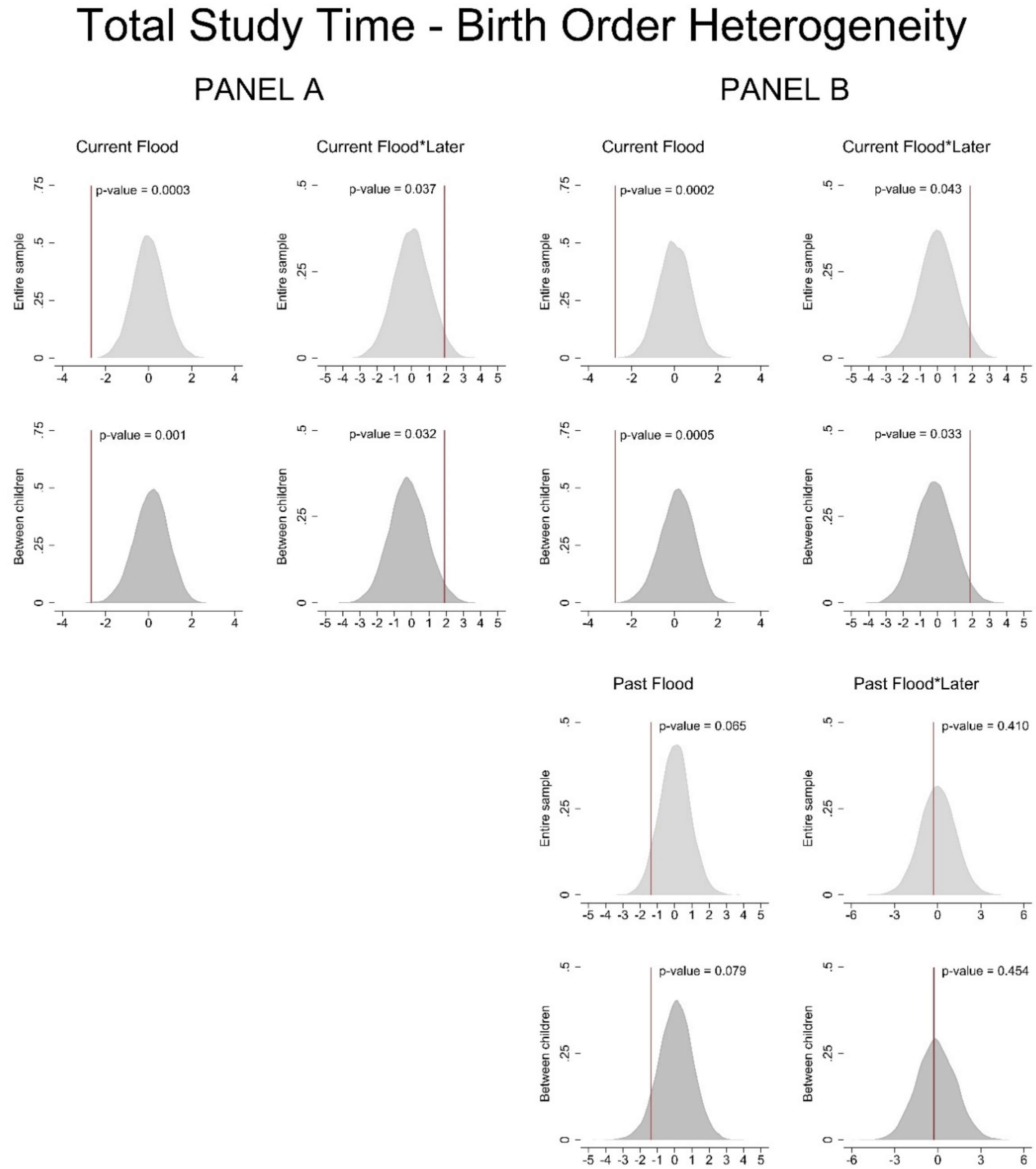

Figure D3.3. Randomization Inference Distributions – Total Study Time: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

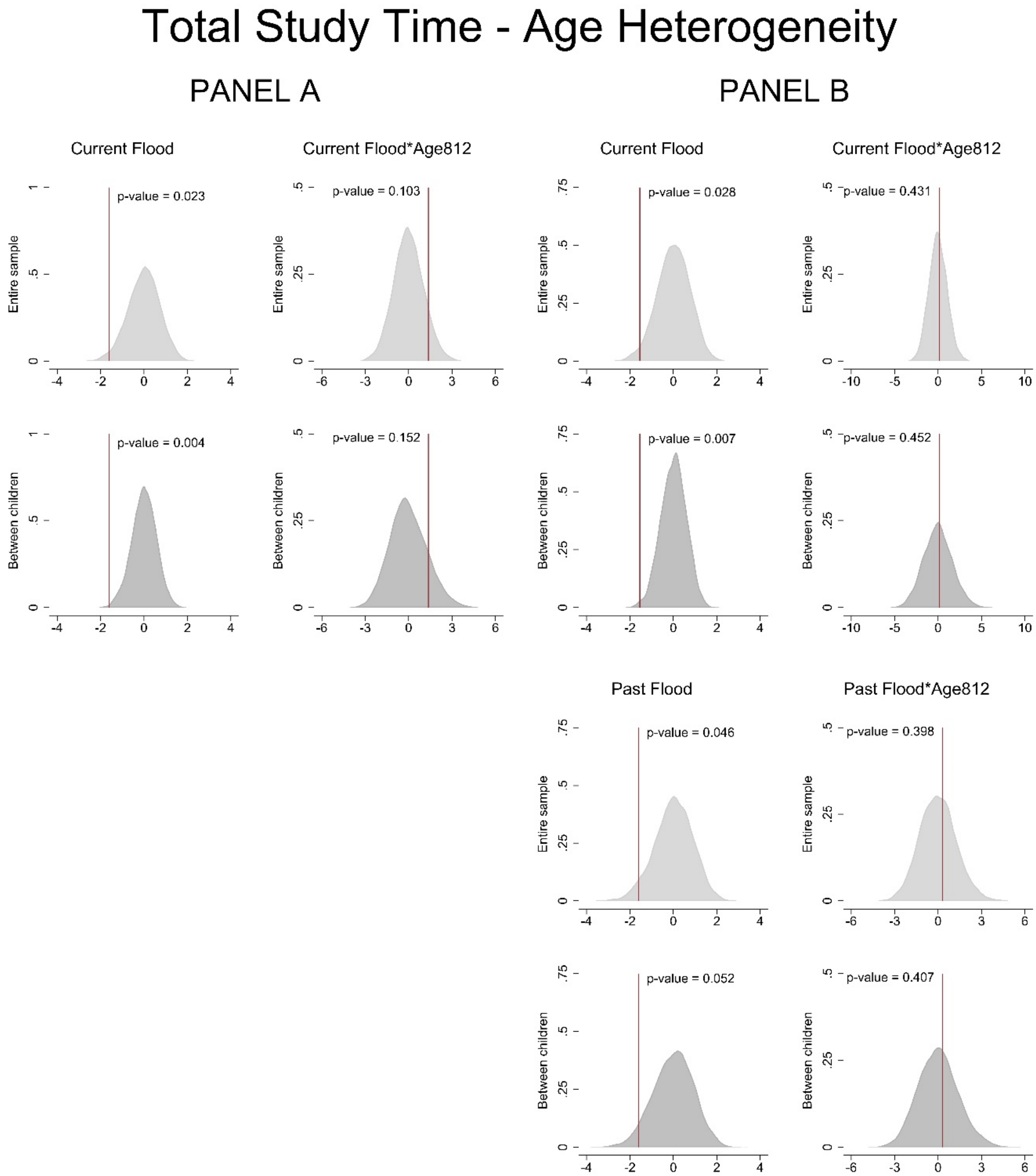

Figure D3.4. Randomization Inference Distributions – Total Study Time: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

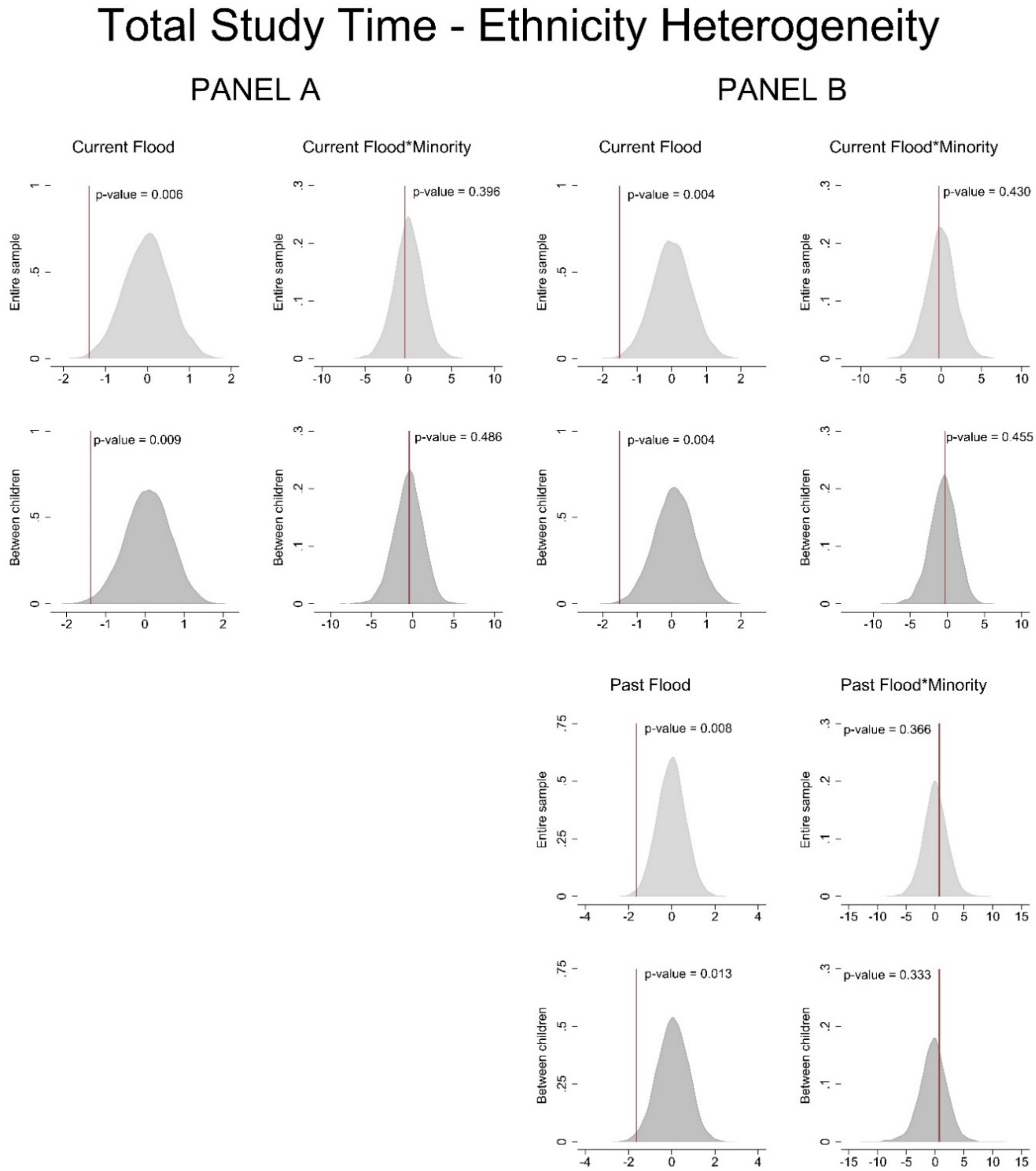

Figure D3.5. Randomization Inference Distributions – Total Study Time: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

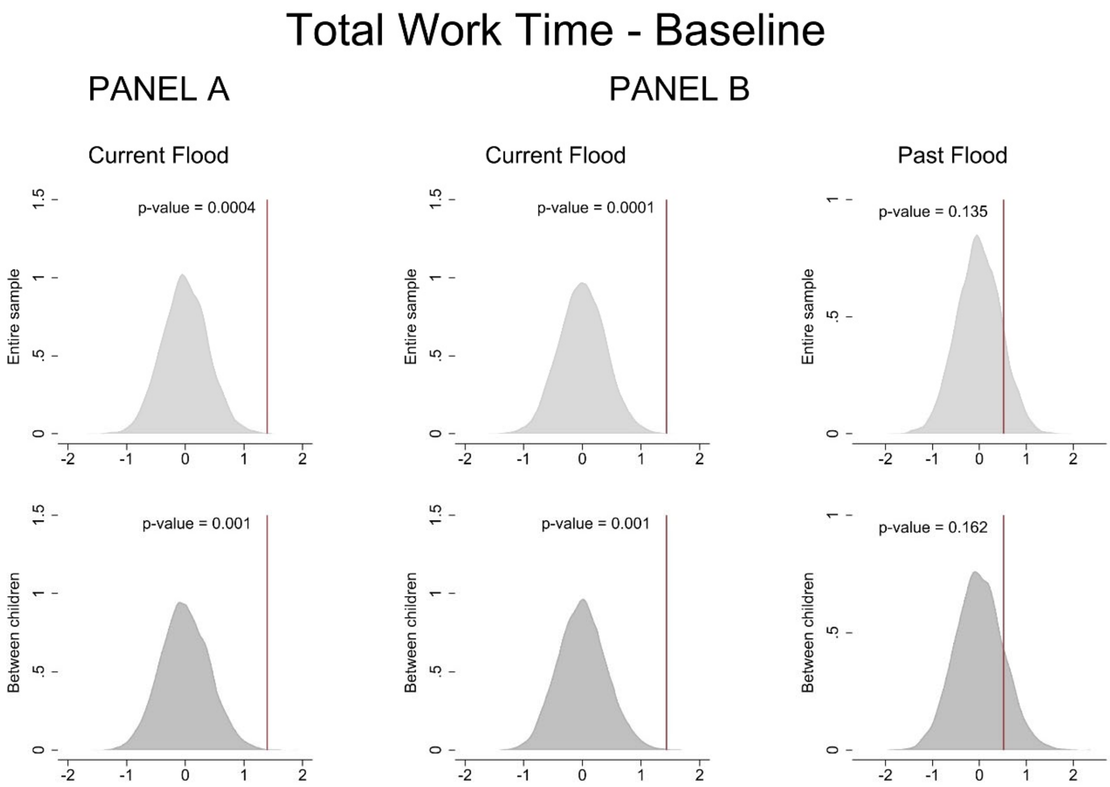

Figure D4.1. Randomization Inference Distributions – Total Work Time: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

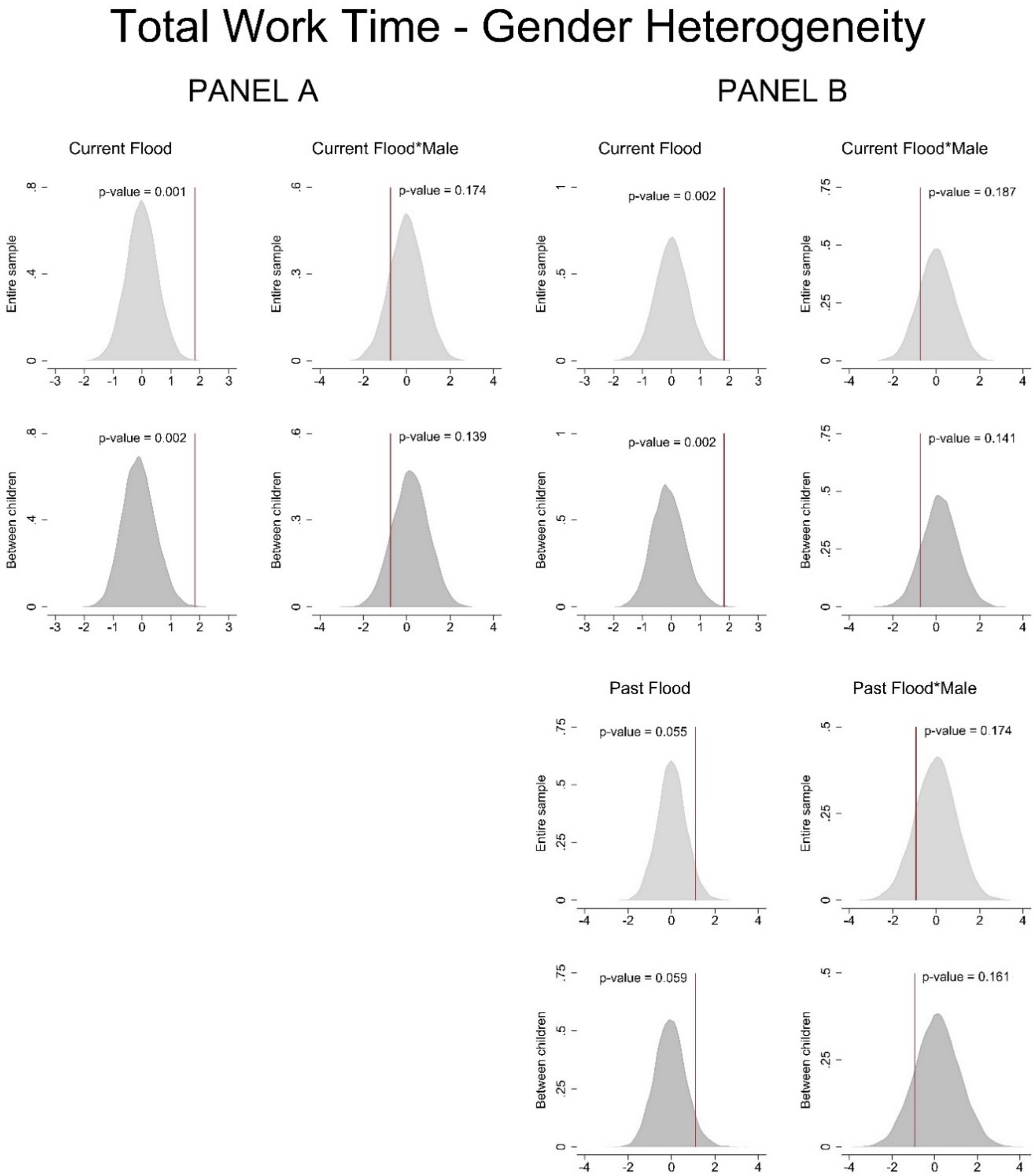

Figure D4.2. Randomization Inference Distributions – Total Work Time: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

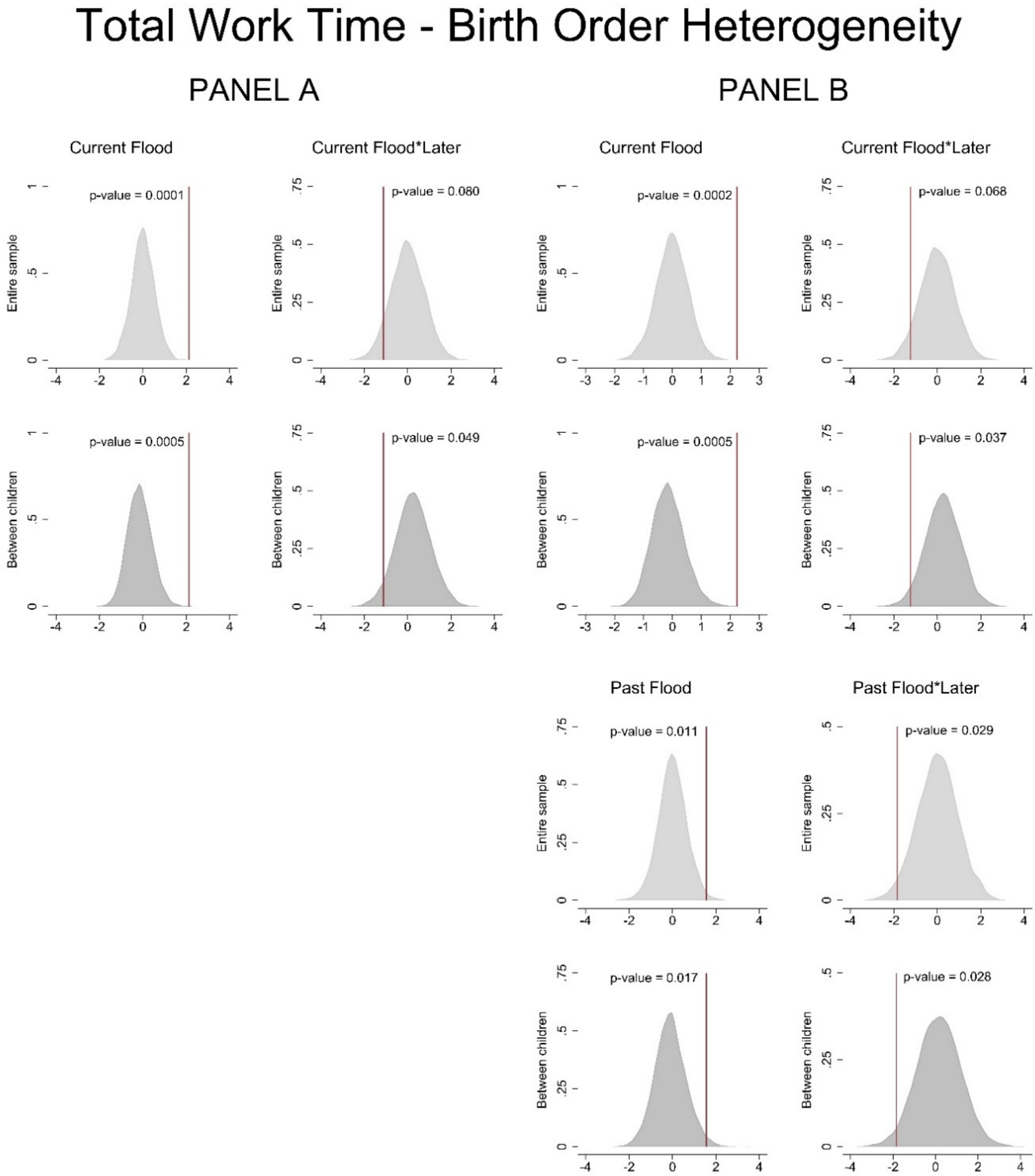

Figure D4.3. Randomization Inference Distributions – Total Work Time: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

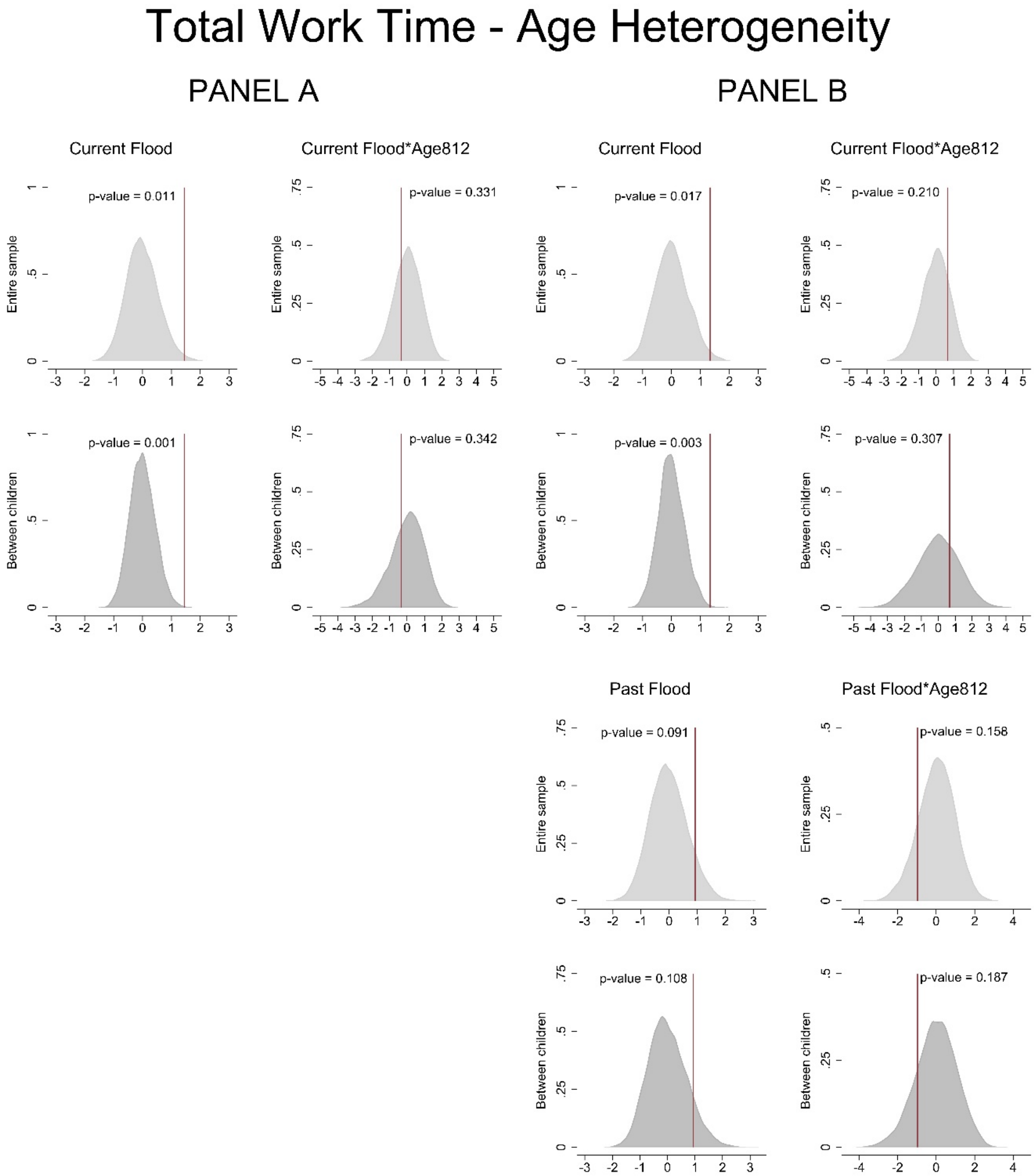

Figure D4.4. Randomization Inference Distributions – Total Work Time: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

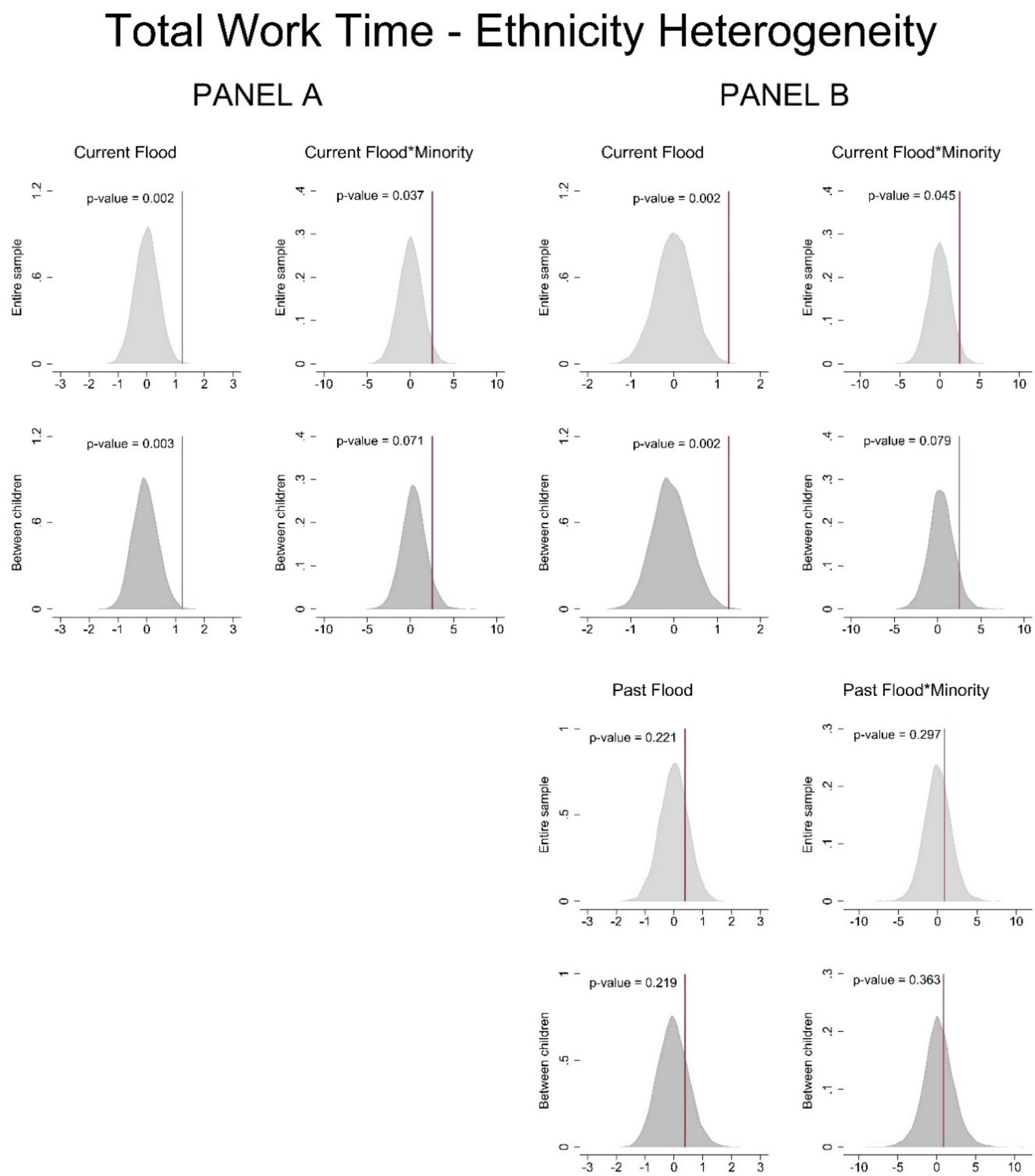

Figure D4.5. Randomization Inference Distributions – Total Work Time: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

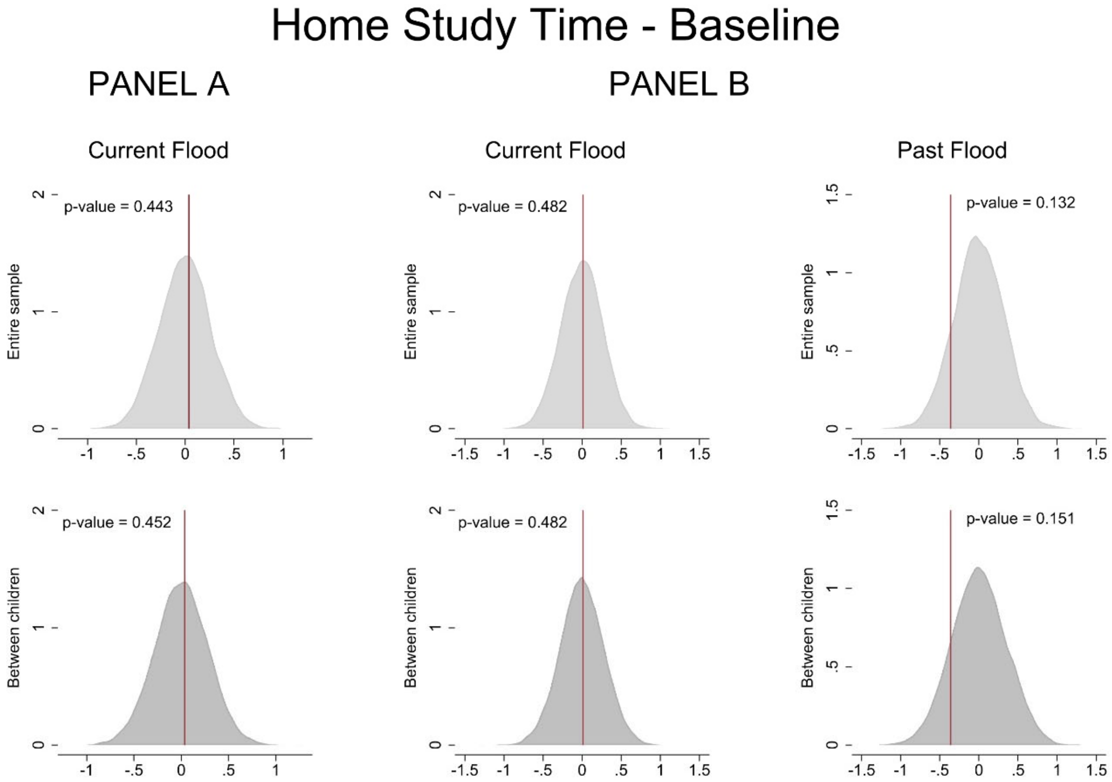

Figure D5.1. Randomization Inference Distributions – Home Study Time: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

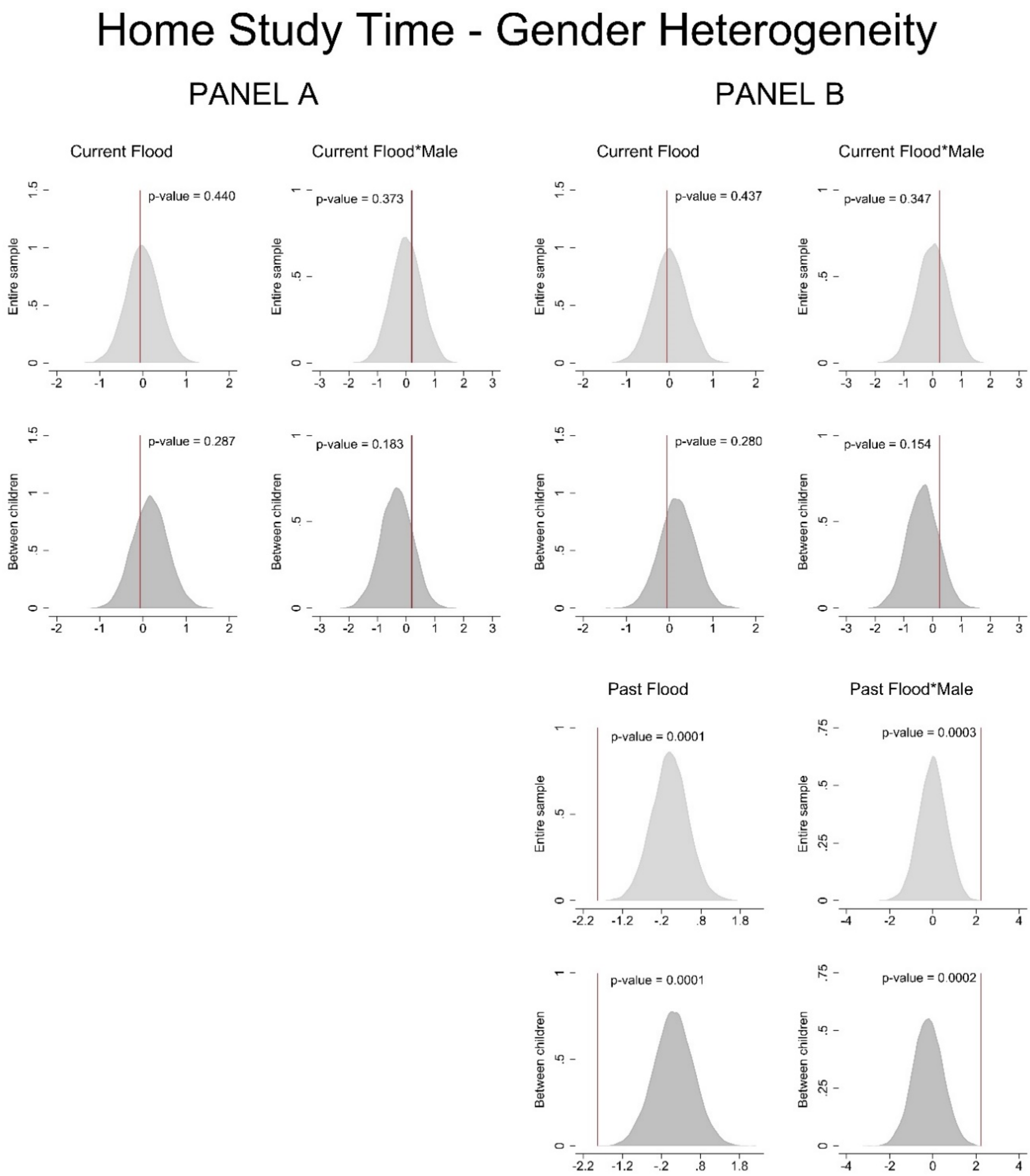

Figure D5.2. Randomization Inference Distributions – Home Study Time: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

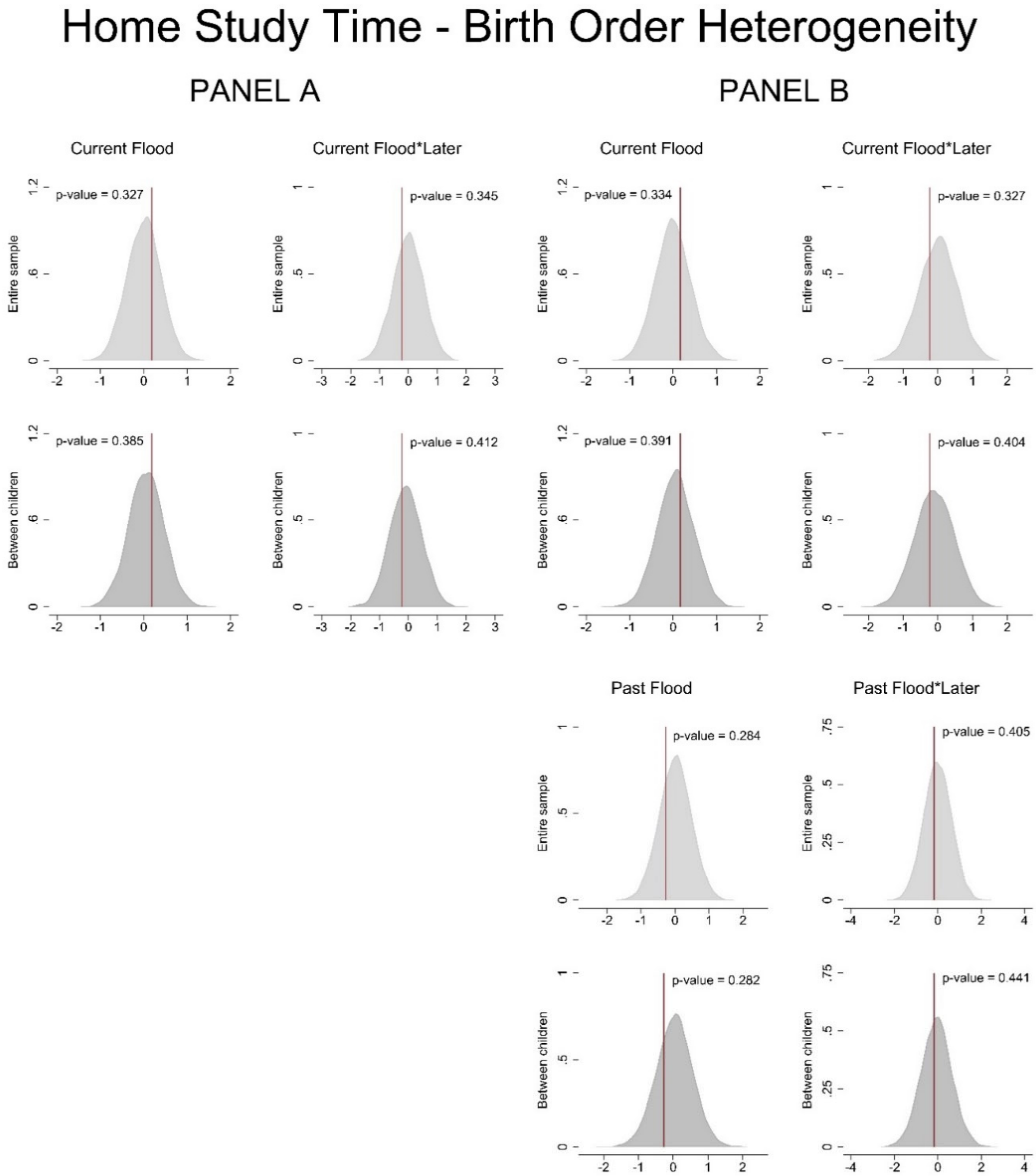

Figure D5.3. Randomization Inference Distributions – Home Study Time: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

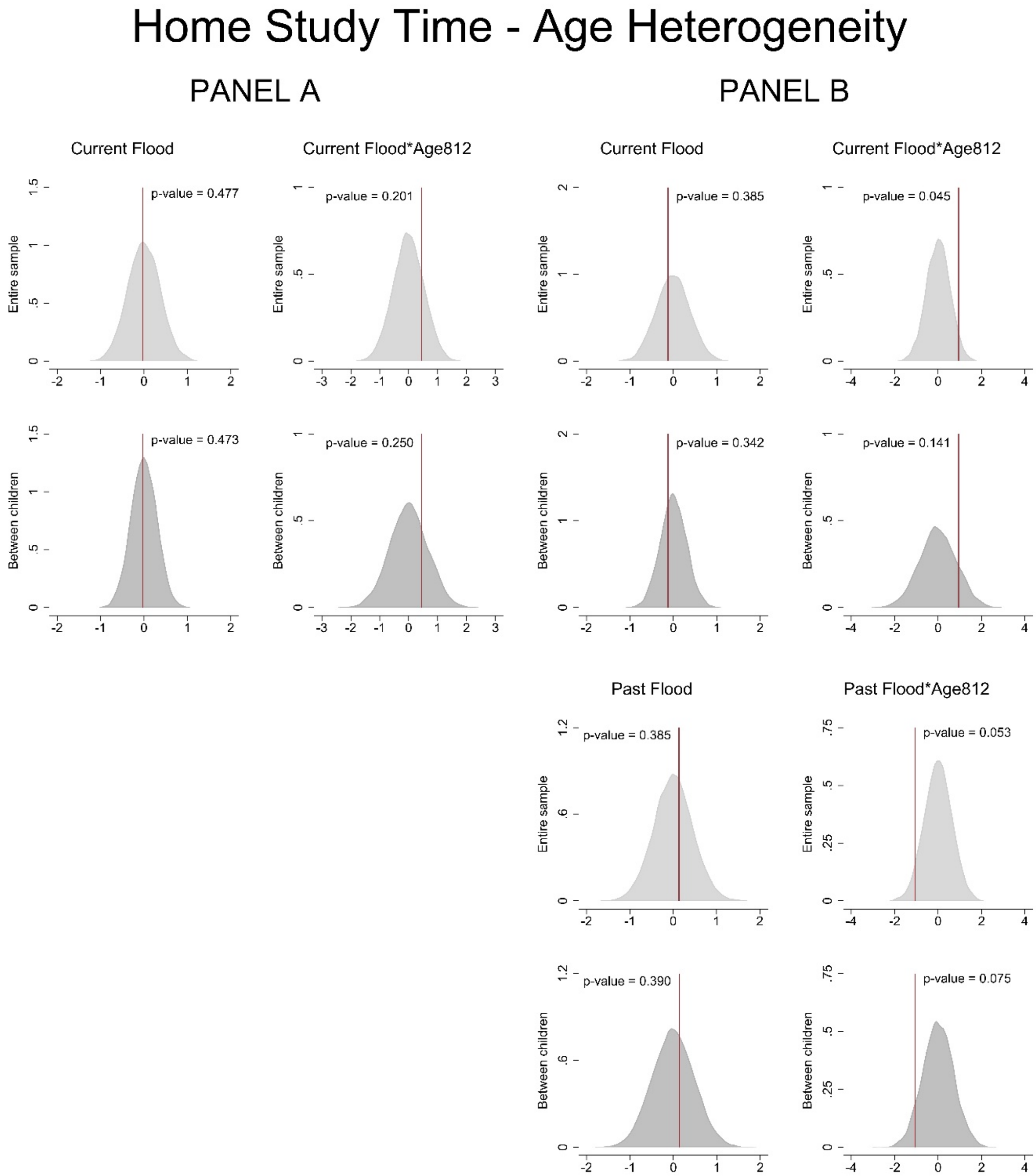

Figure D5.4. Randomization Inference Distributions – Home Study Time: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

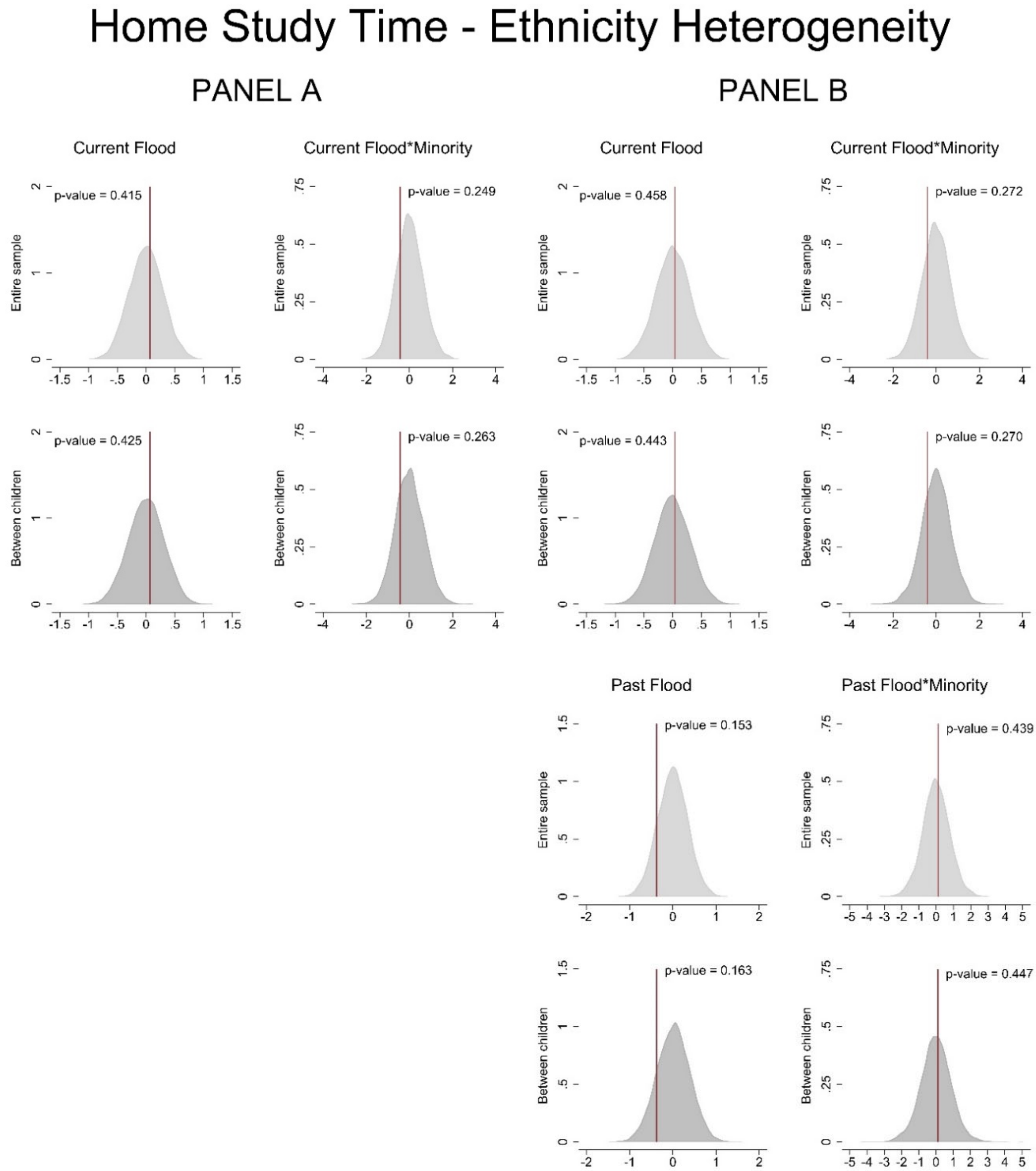

Figure D5.5. Randomization Inference Distributions – Home Study Time: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

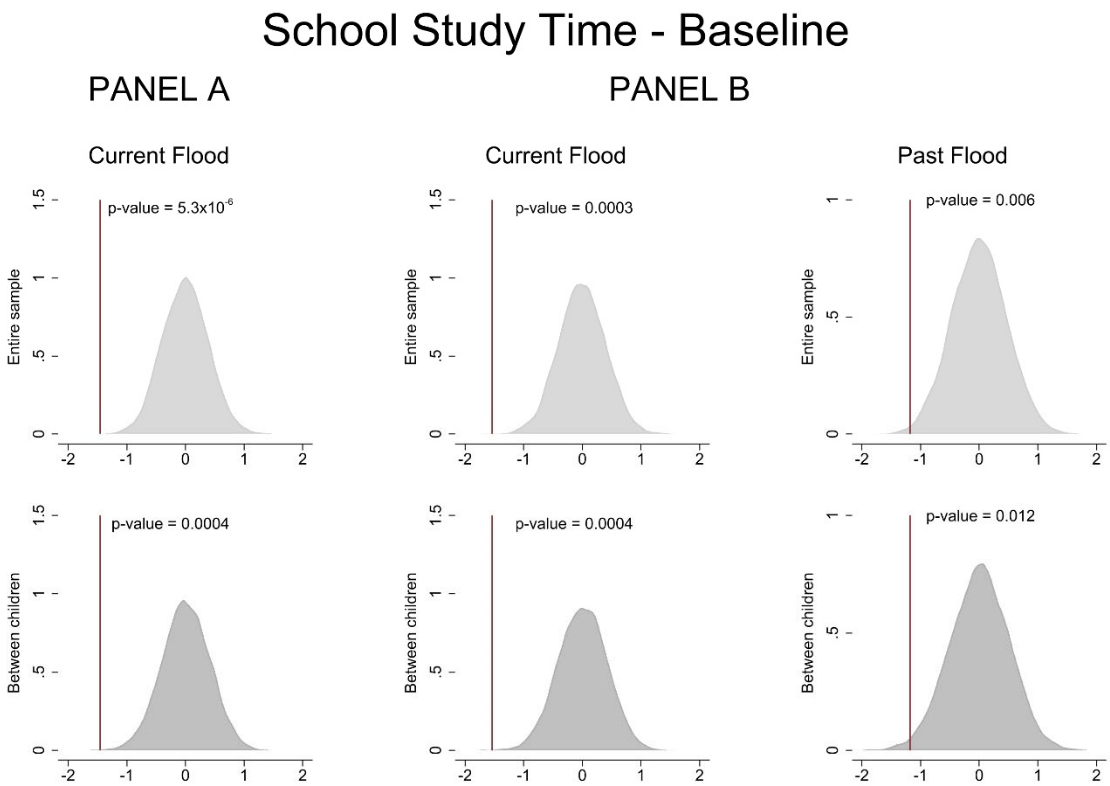

Figure D6.1. Randomization Inference Distributions – School Study Time: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

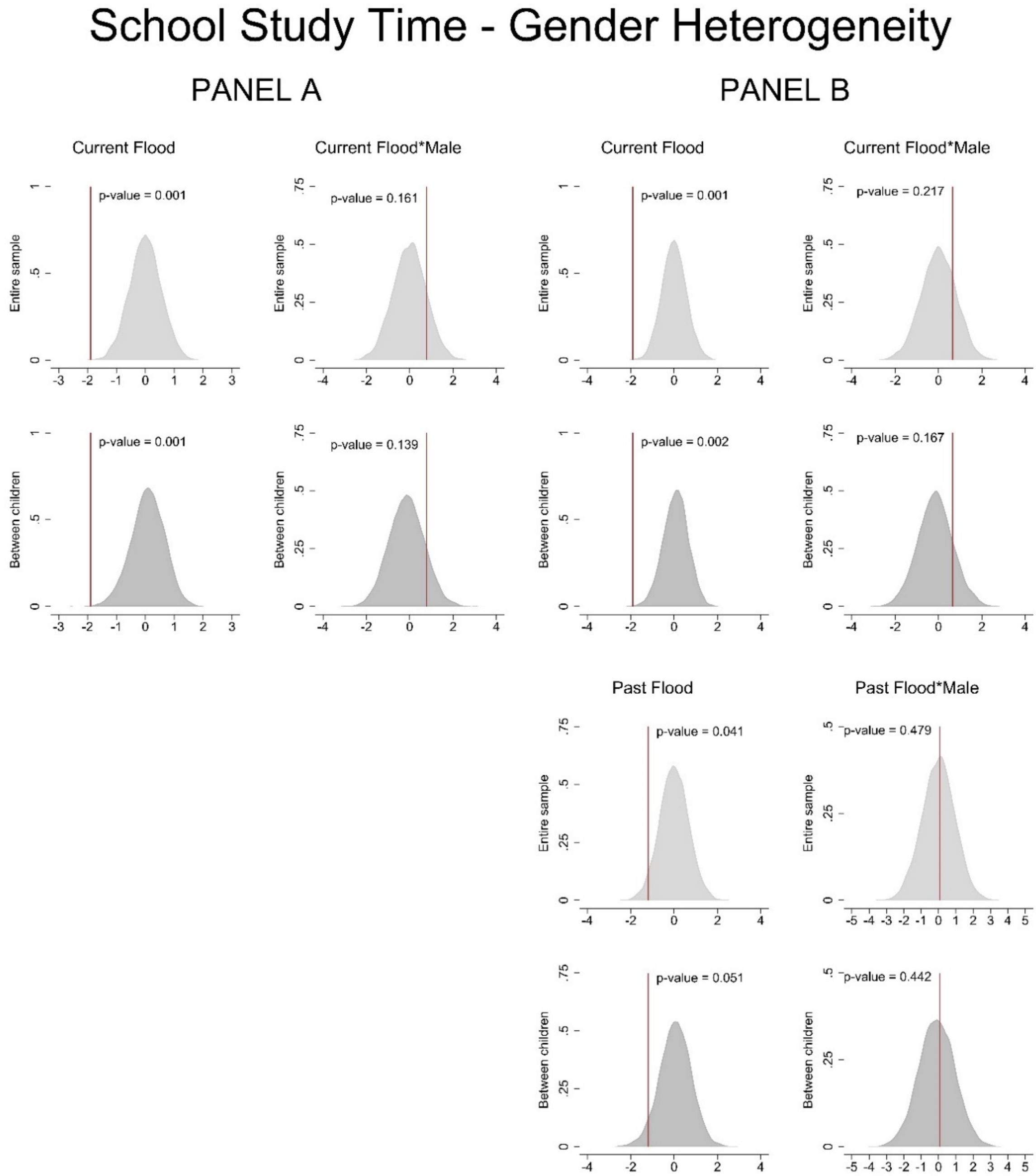

Figure D6.2. Randomization Inference Distributions – School Study Time: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

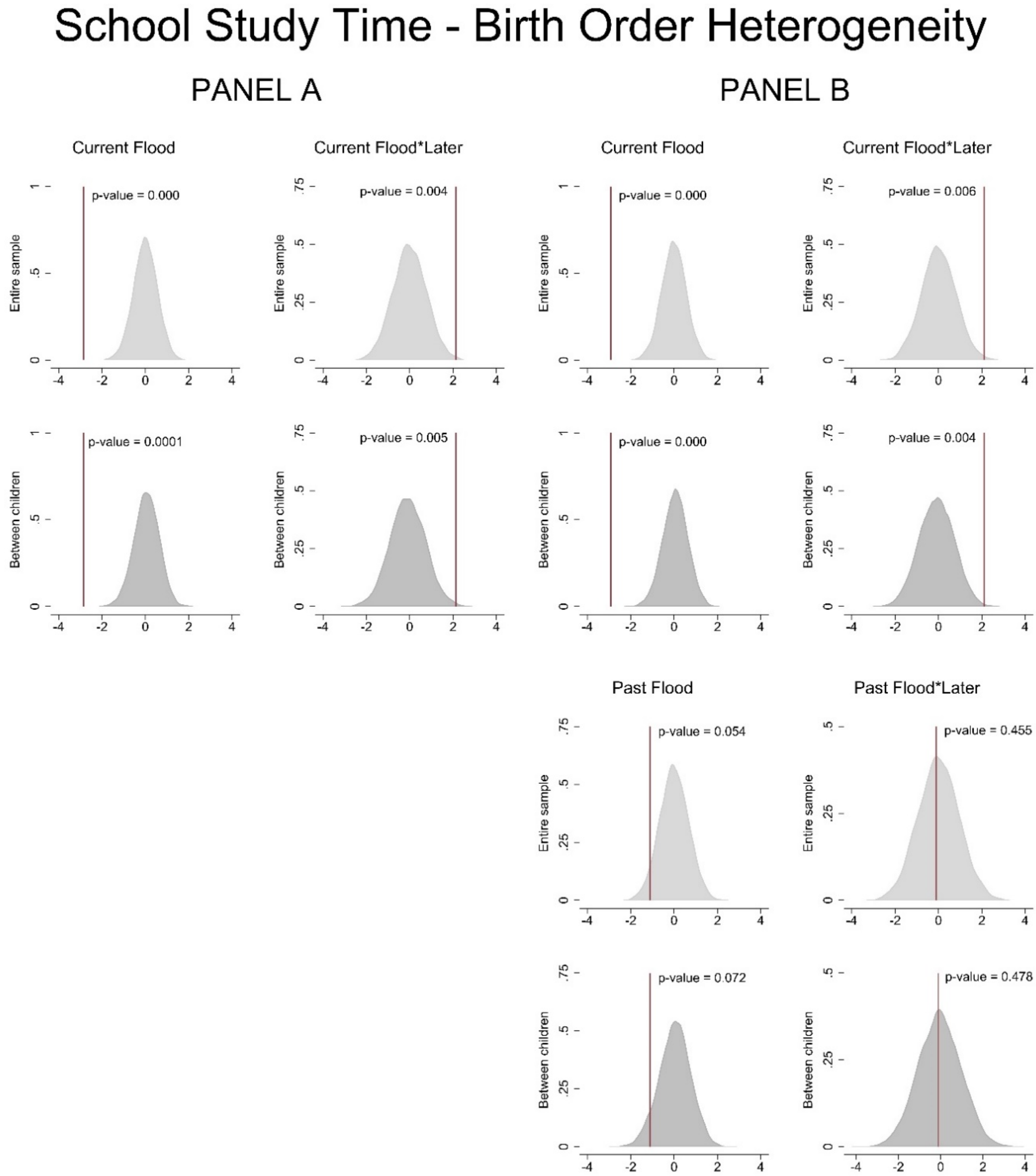

Figure D6.3. Randomization Inference Distributions – School Study Time: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

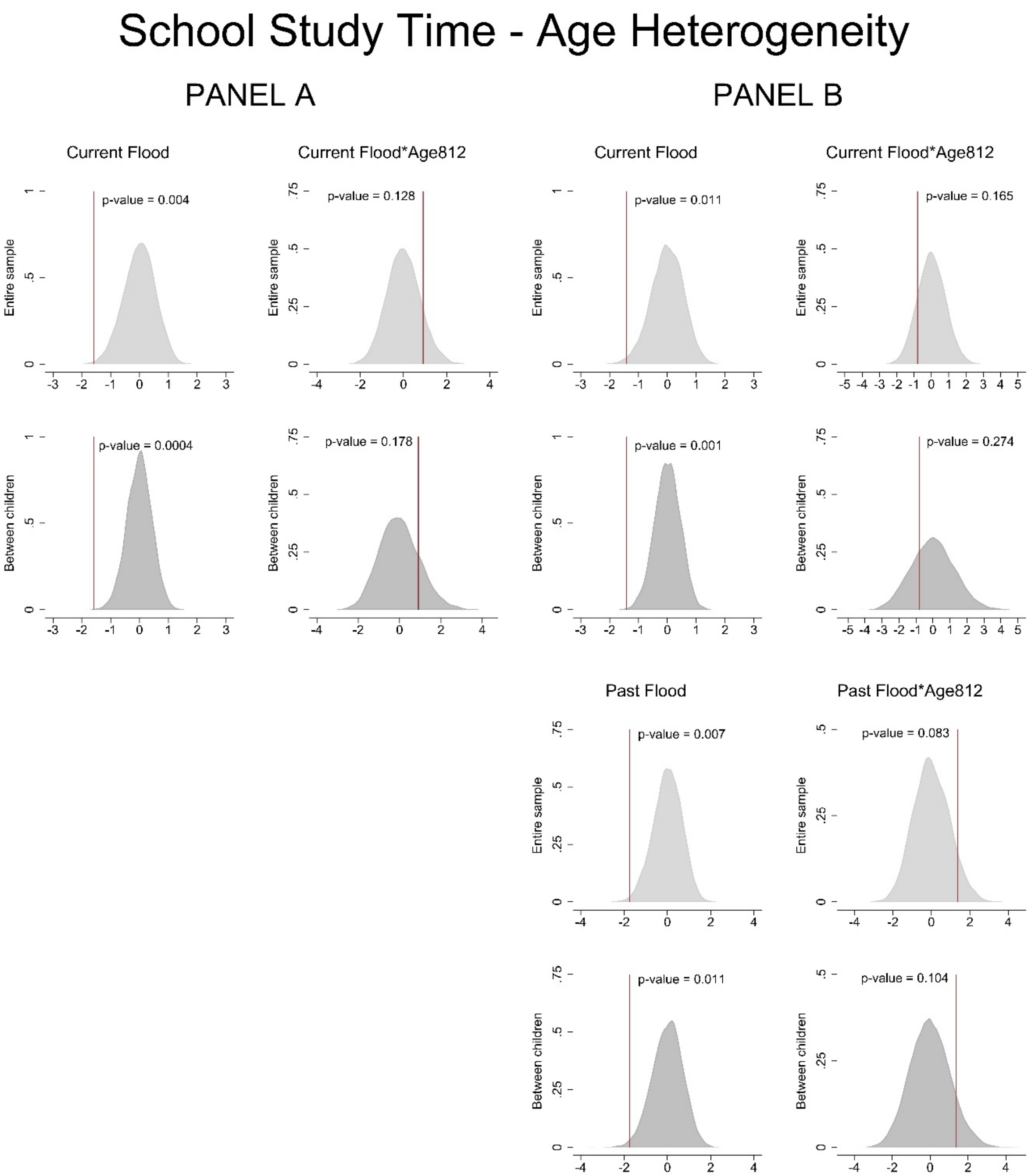

Figure D6.4. Randomization Inference Distributions – School Study Time: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

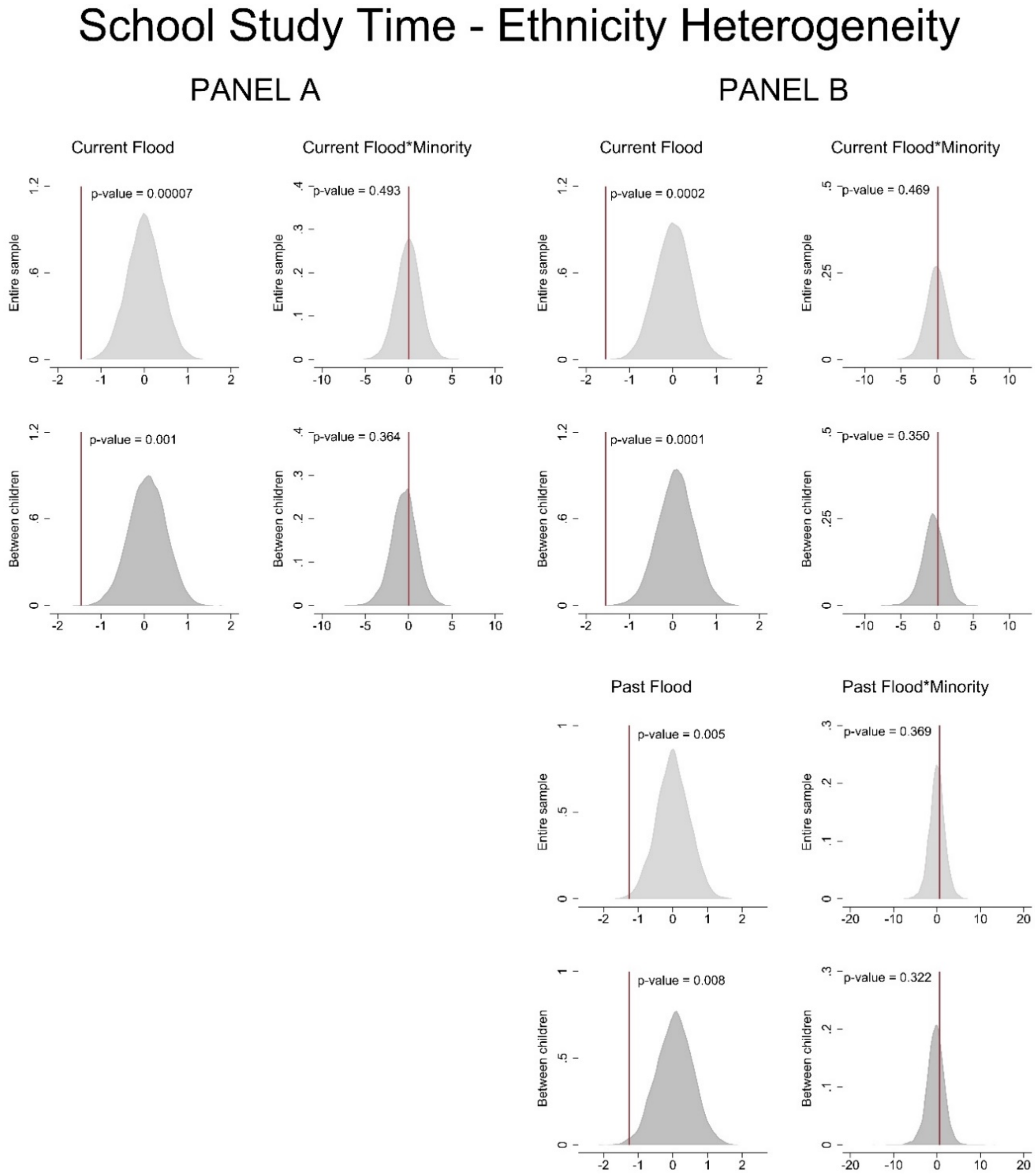

Figure D6.5. Randomization Inference Distributions – School Study Time: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

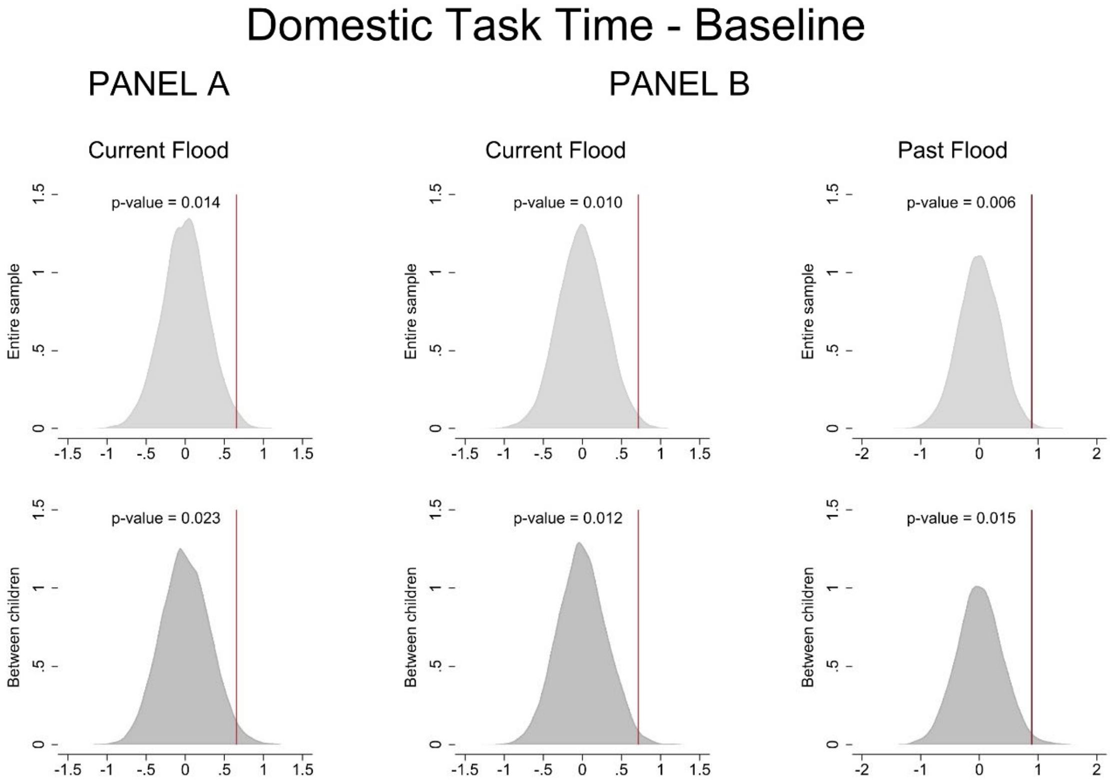

Figure D7.1. Randomization Inference Distributions – Domestic Task Time: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

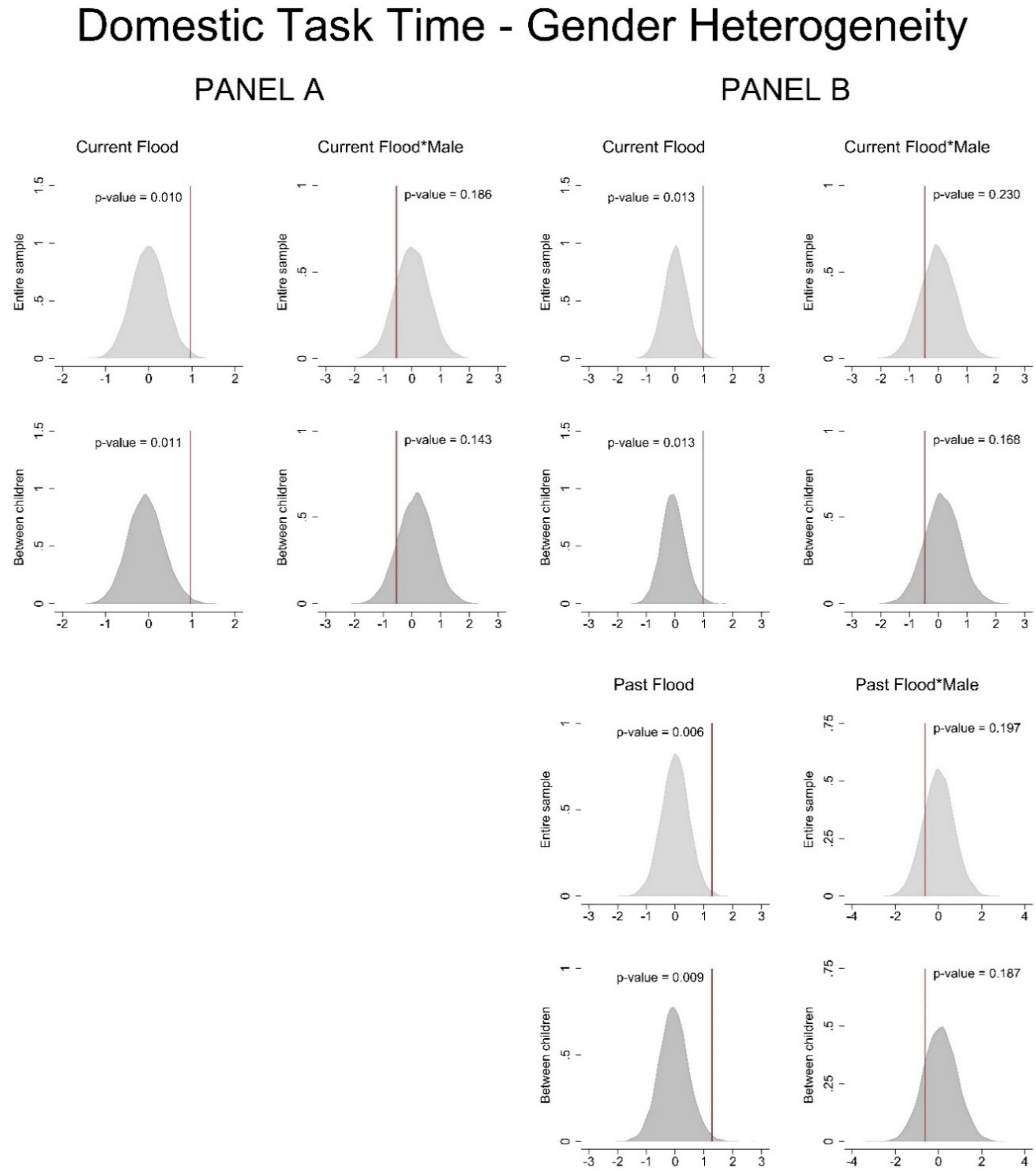

Figure D7.2. Randomization Inference Distributions – Domestic Task Time: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

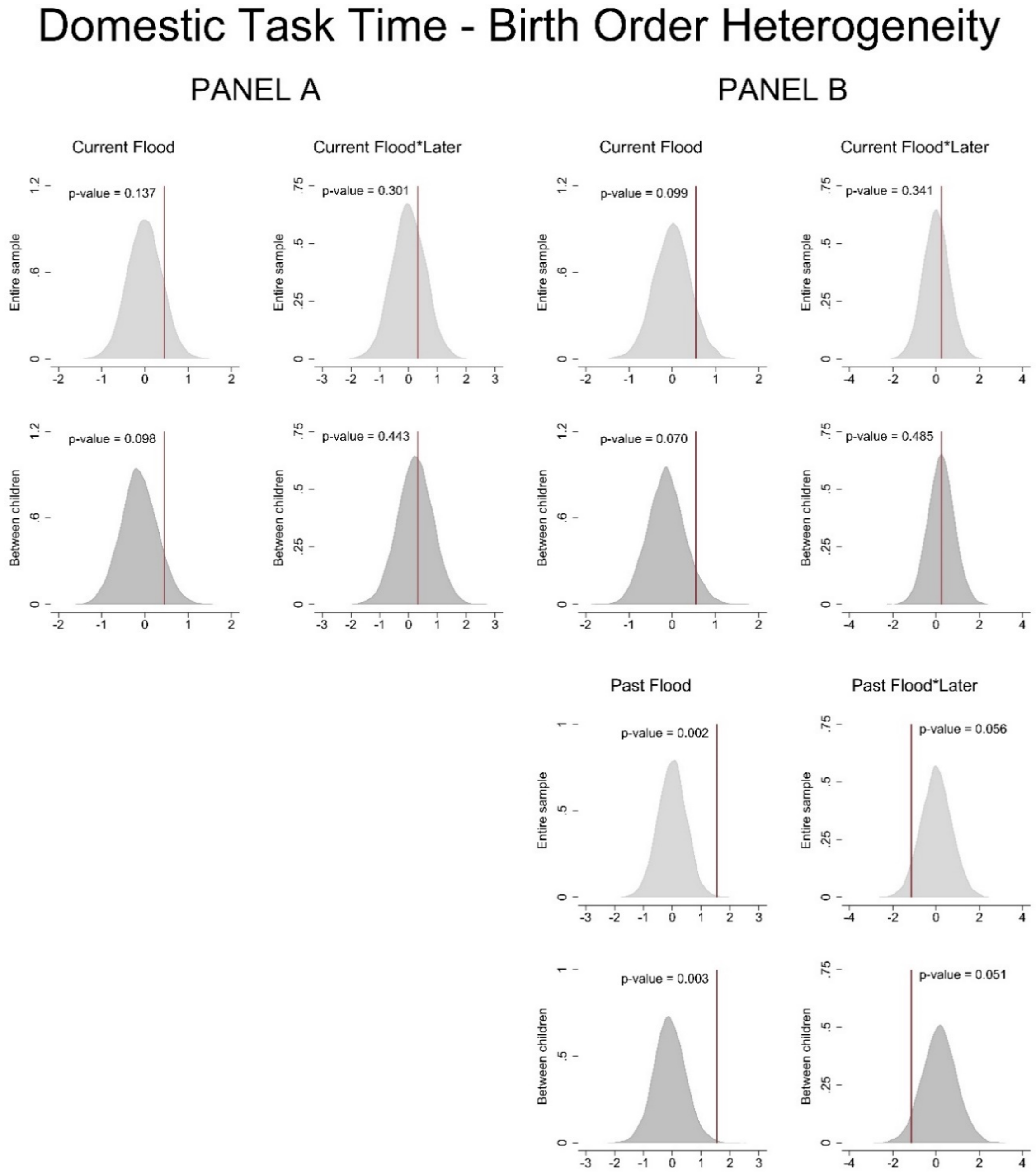

Figure D7.3. Randomization Inference Distributions – Domestic Task Time: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

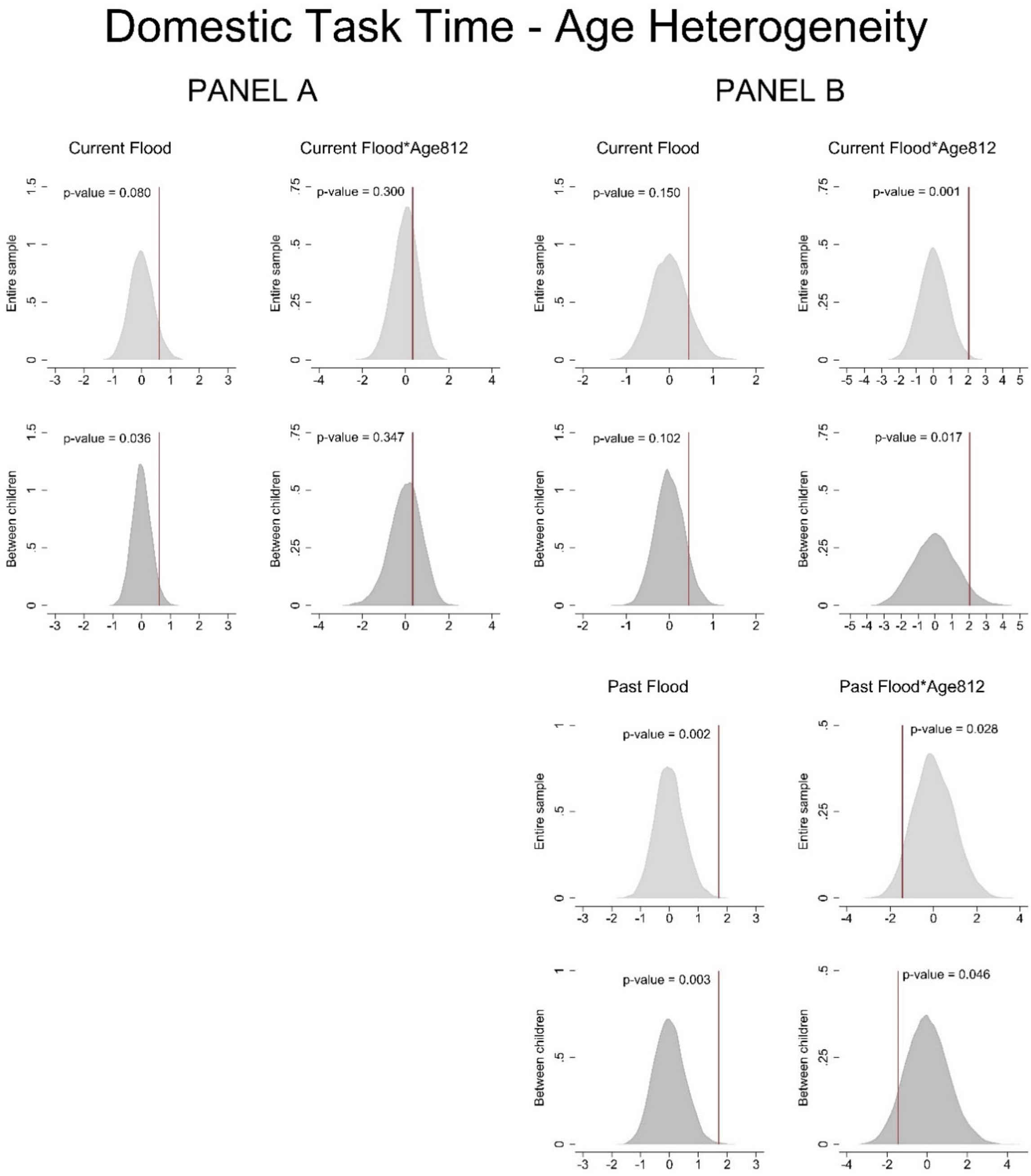

Figure D7.4. Randomization Inference Distributions – Domestic Task Time: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

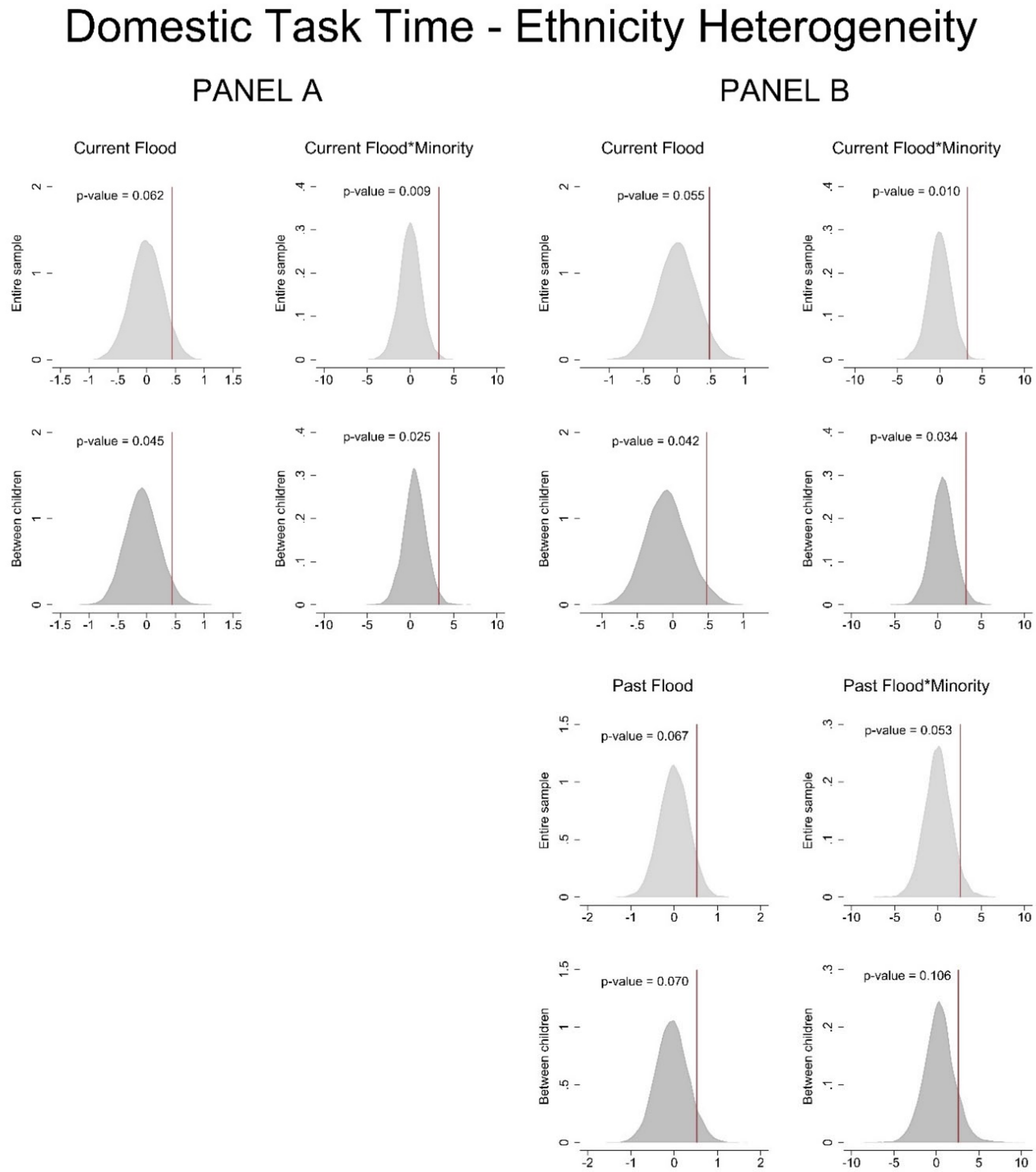

Figure D7.5. Randomization Inference Distributions – Domestic Task Time: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

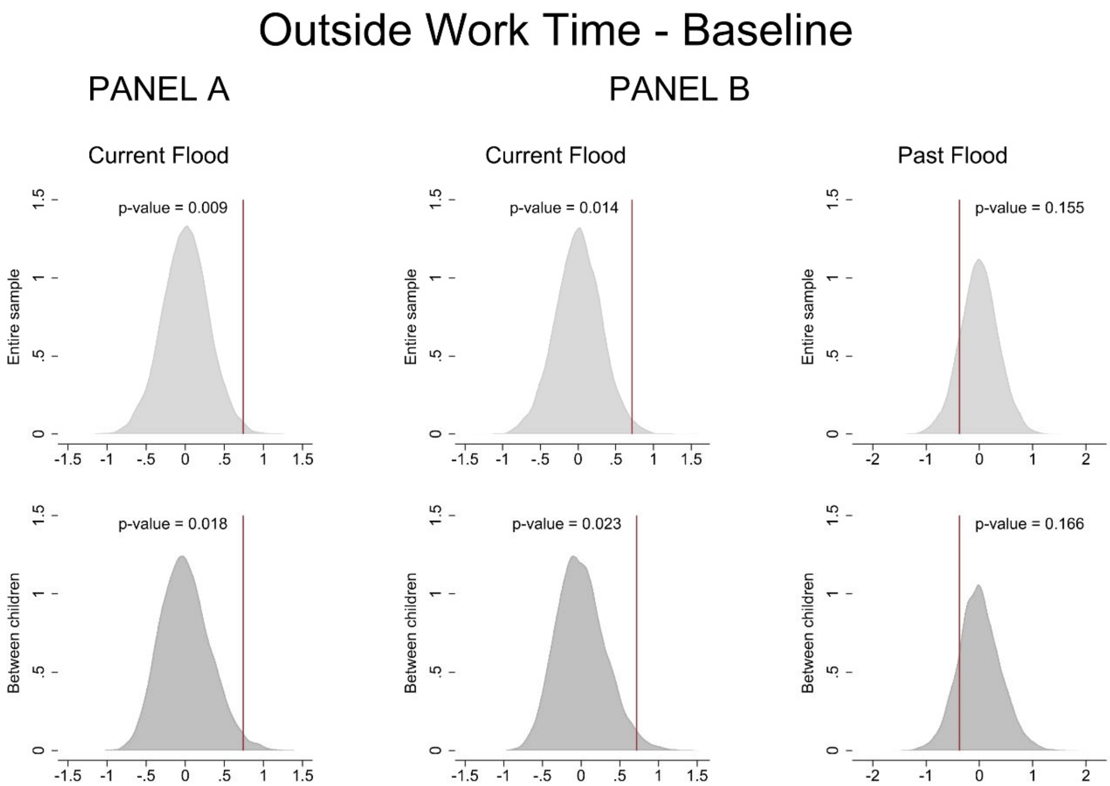

Figure D8.1. Randomization Inference Distributions – Outside Work Time: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

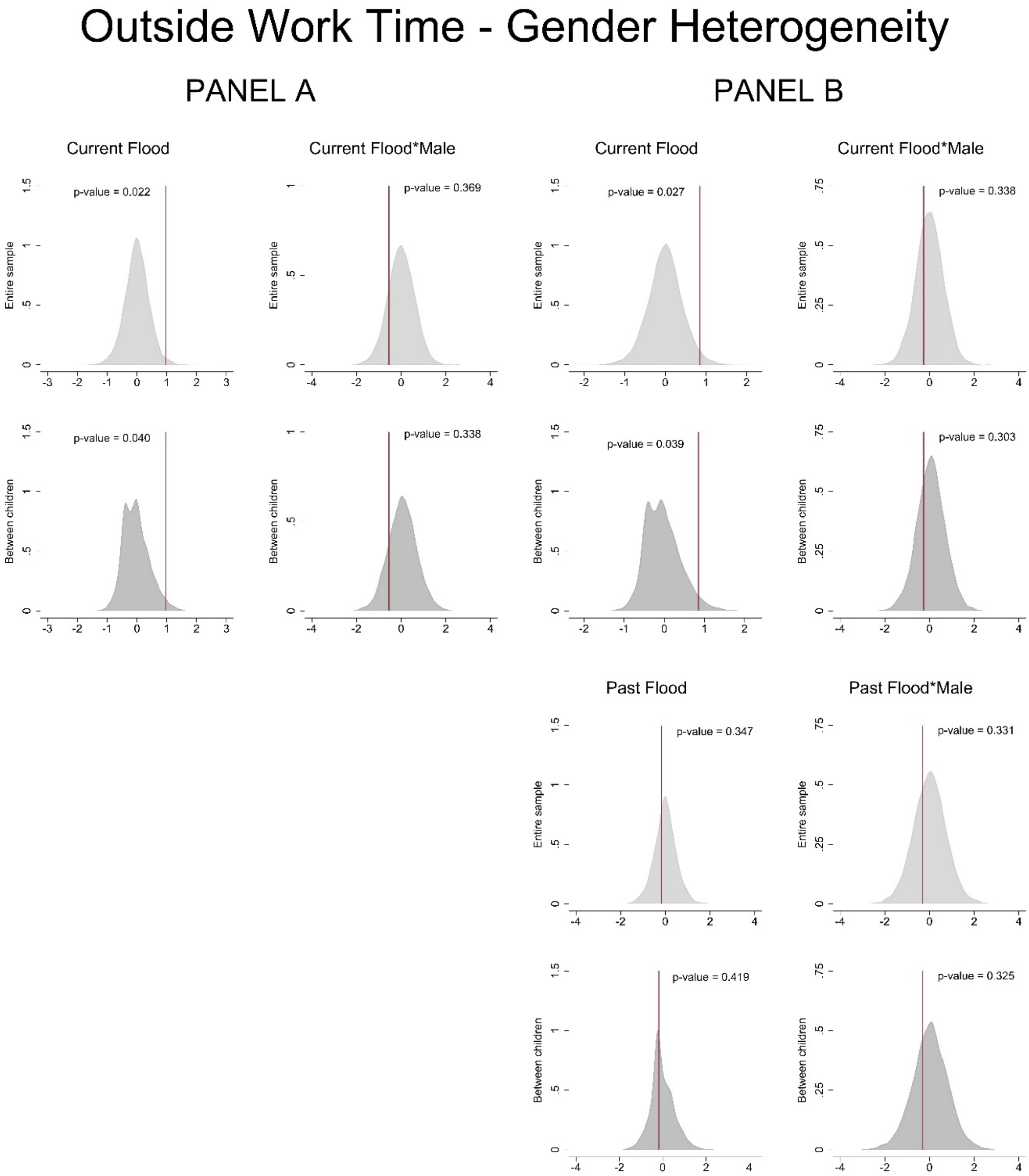

Figure D8.2. Randomization Inference Distributions – Outside Work Time: Gender Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the male dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

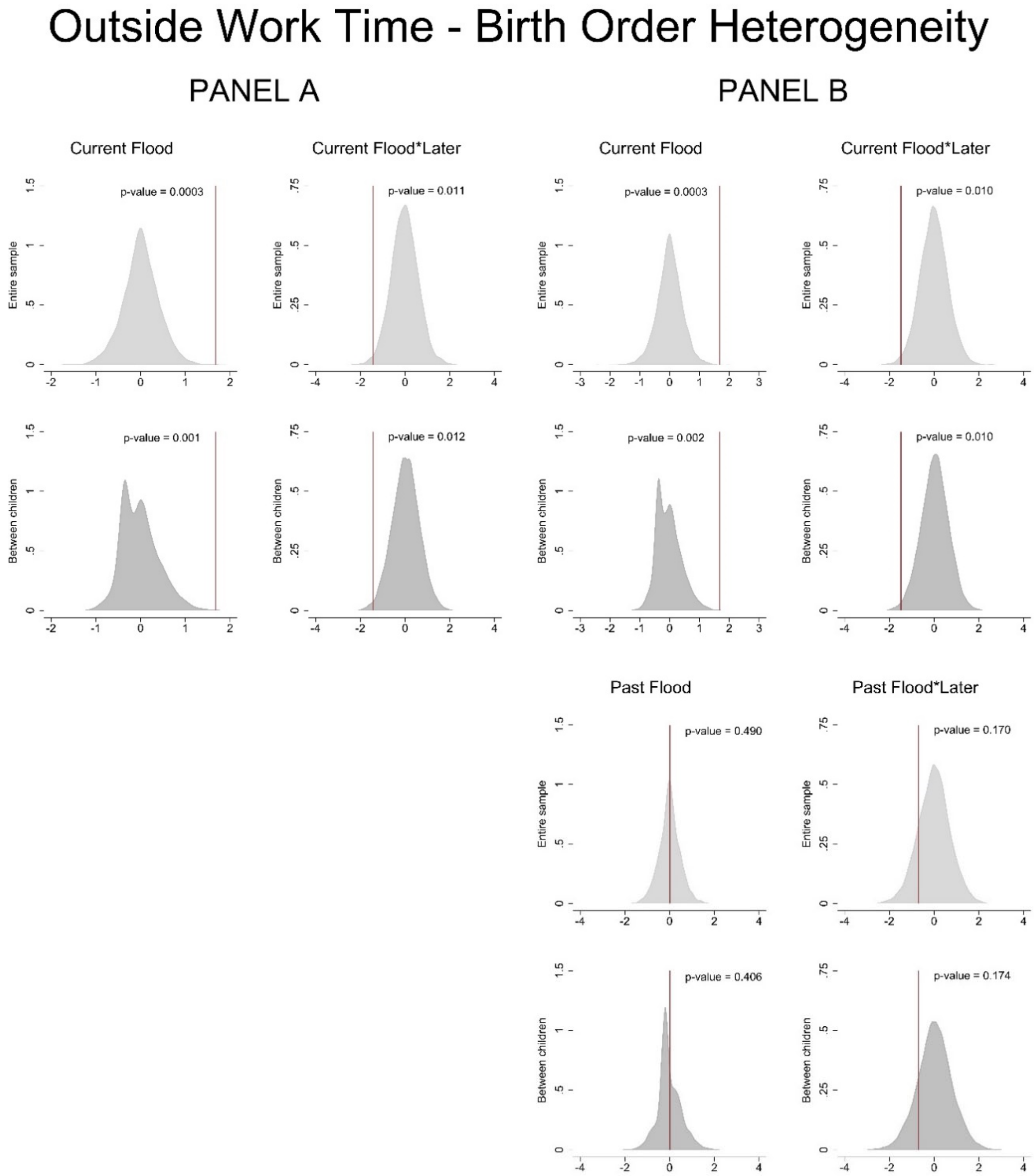

Figure D8.3. Randomization Inference Distributions – Outside Work Time: Birth Order Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the later-born dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

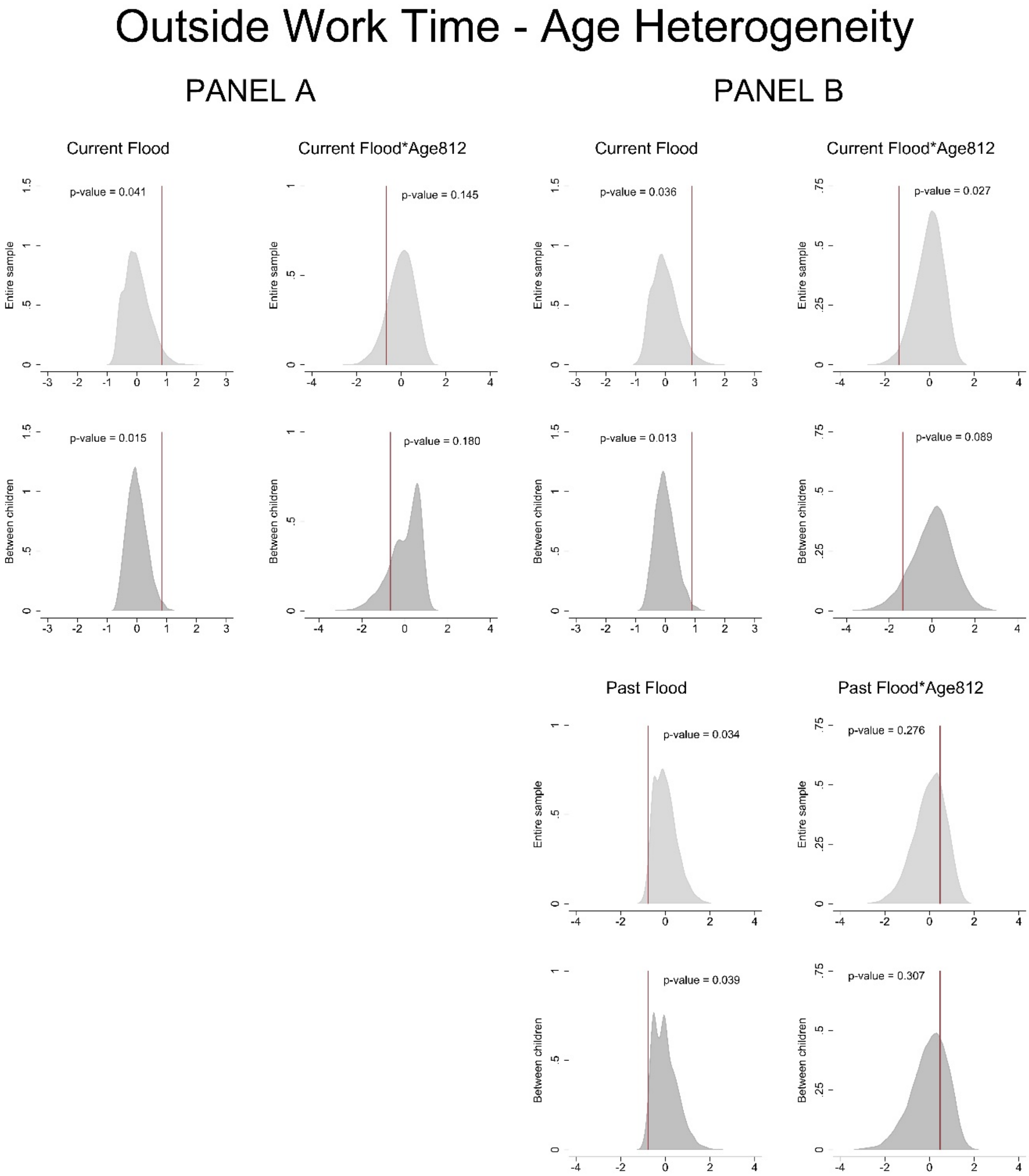

Figure D8.4. Randomization Inference Distributions – Outside Work Time: Age Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the age dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

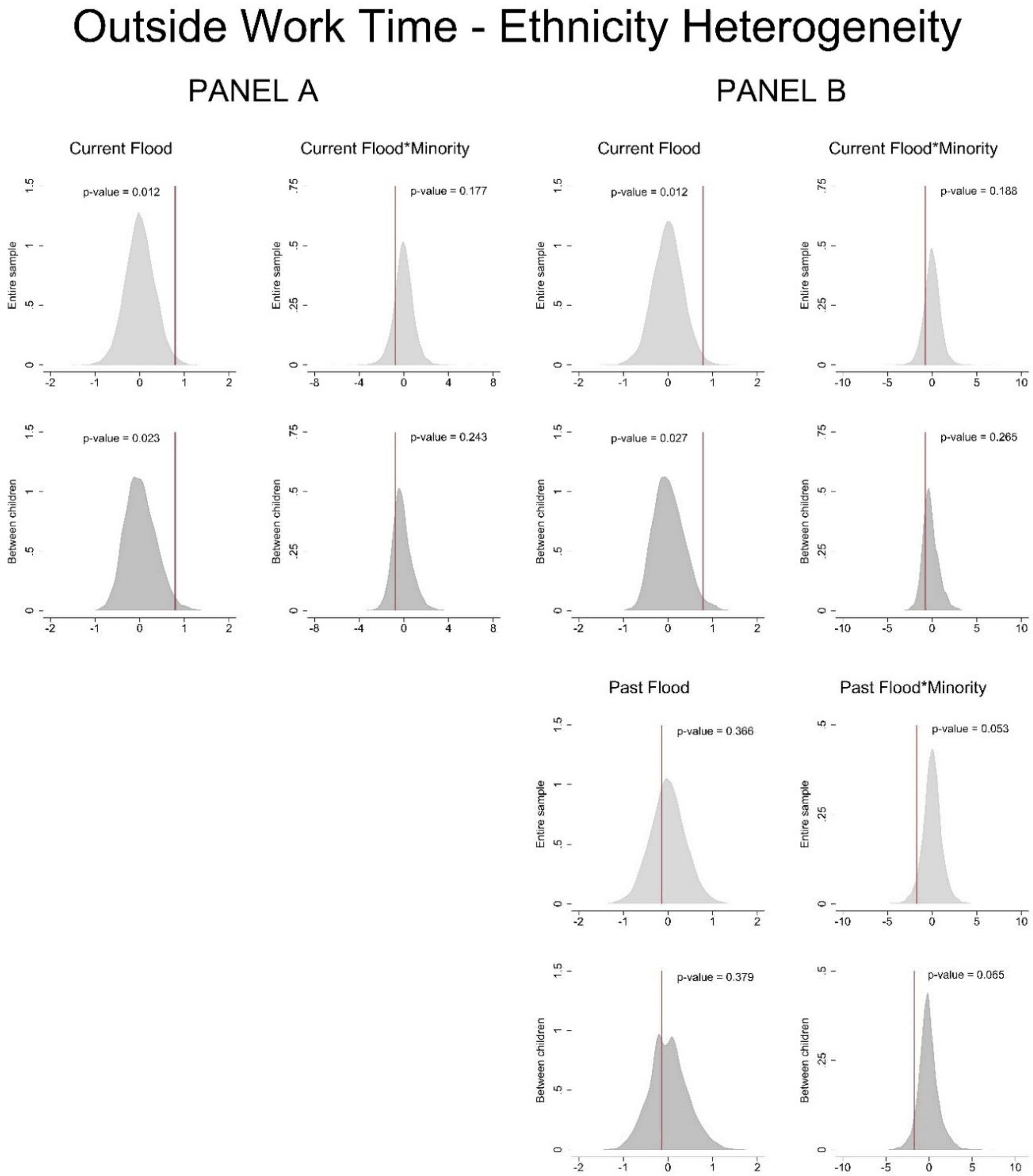

Figure D8.5. Randomization Inference Distributions – Outside Work Time: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

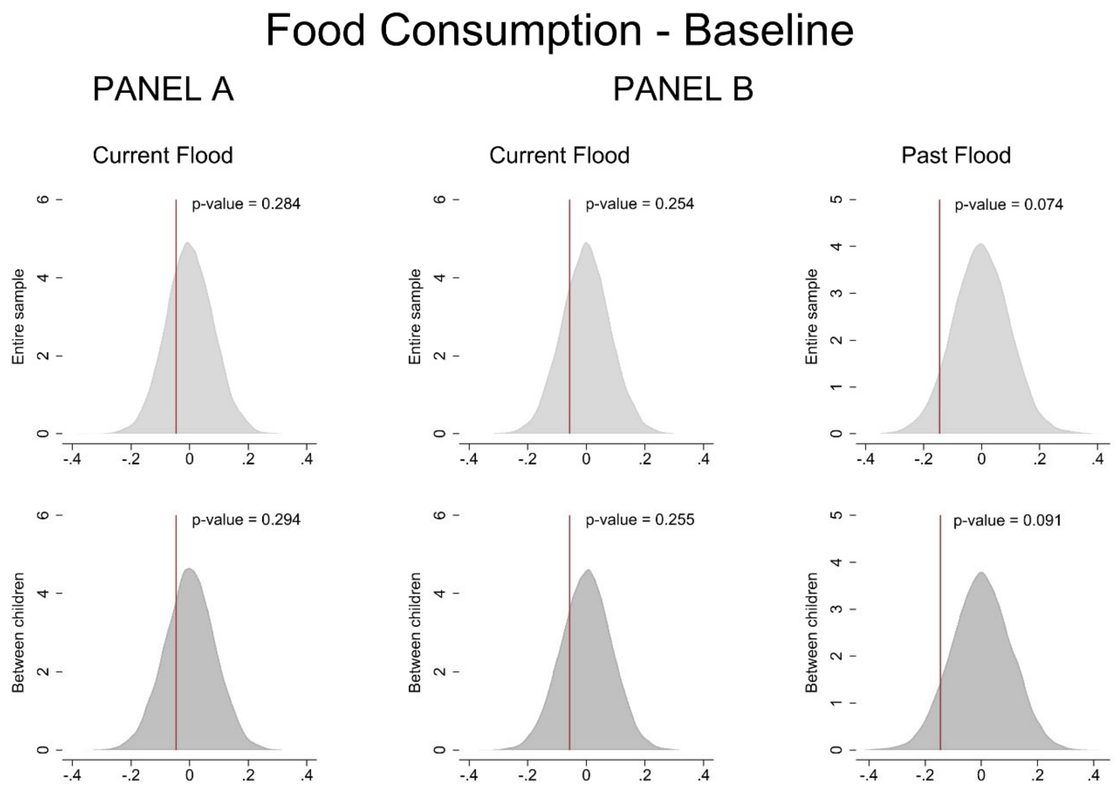

Figure D9.1. Randomization Inference Distributions – Food Consumption: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

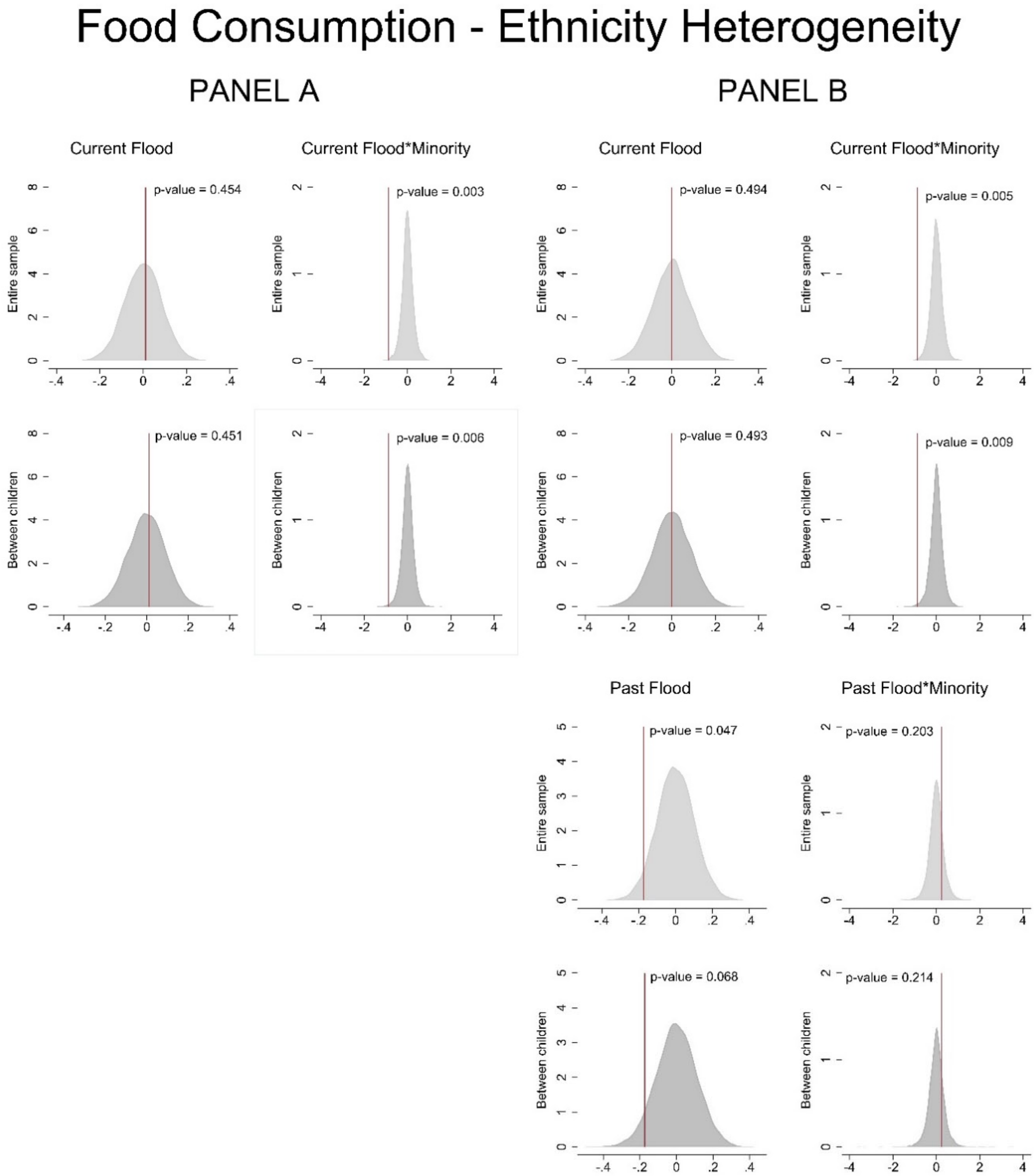

Figure D9.2. Randomization Inference Distributions – Food Consumption: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

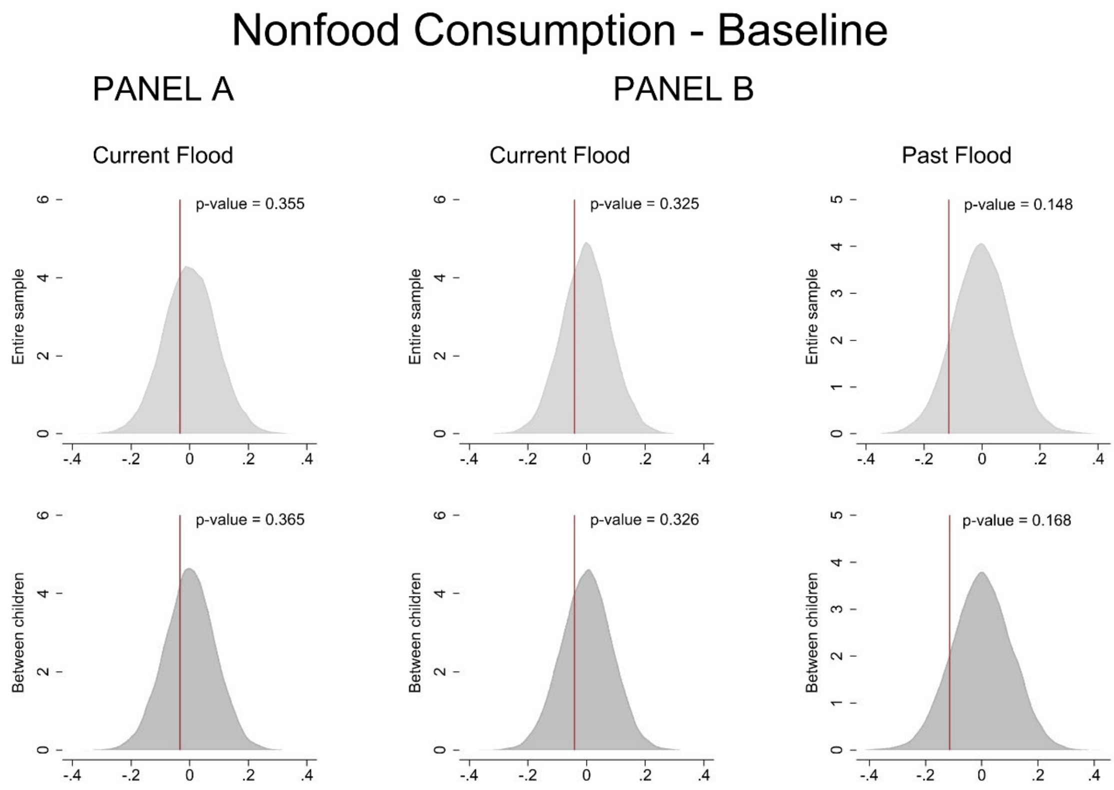

Figure D10.1. Randomization Inference Distributions – Nonfood Consumption: Baseline

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.

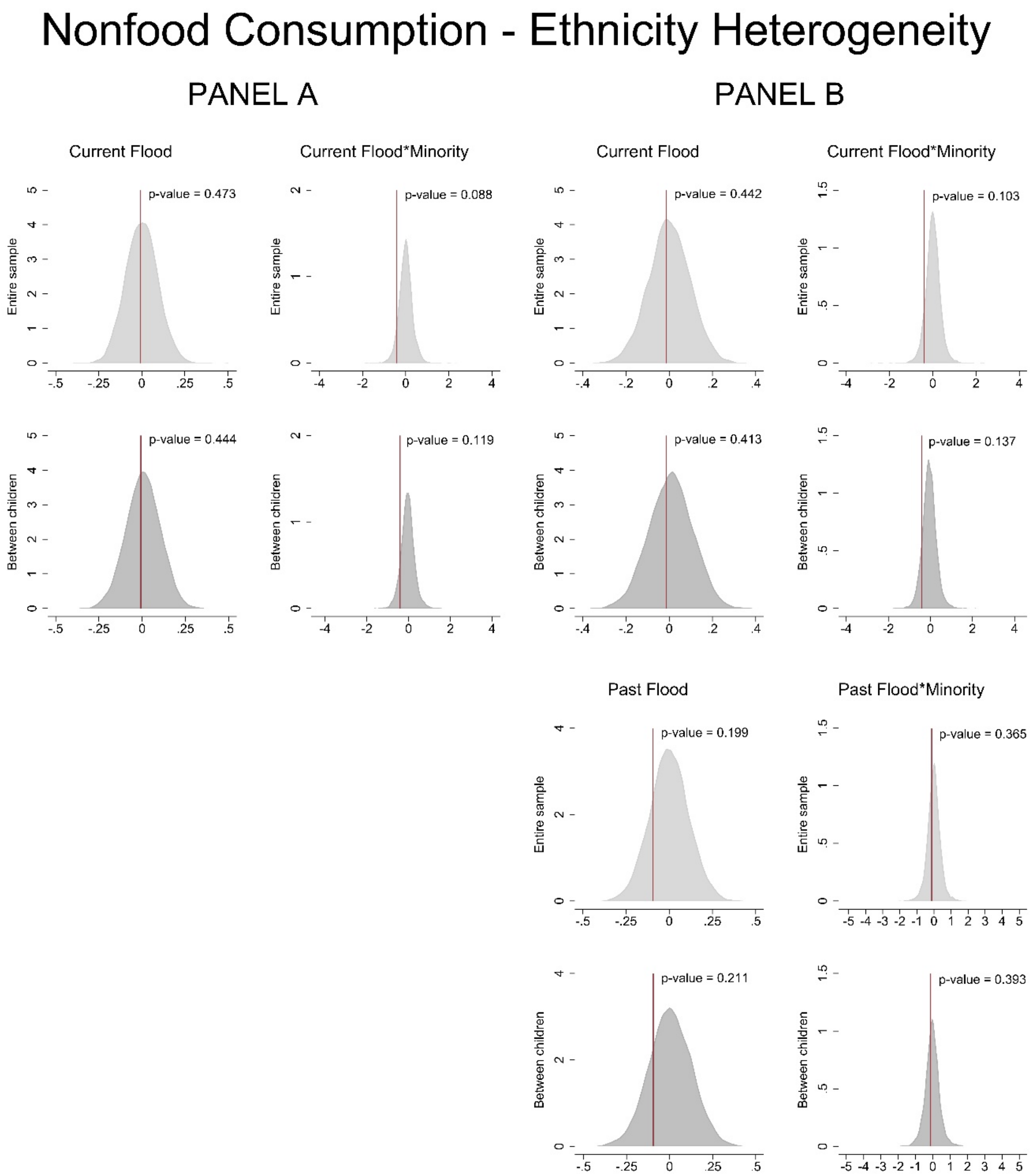

Figure D10.2. Randomization Inference Distributions – Nonfood Consumption: Ethnicity Heterogeneity

NOTES: Each plot represents the distribution of point estimates for both the Current Flood and Past Flood variables by re-estimating Equations 1-2 on randomized placebo datasets. Each distribution corresponds to the single term of flood dummies or the cross term with the minority dummy in Panels A or B for one of two different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p values.