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Heterogeneous impacts of local unemployment rates on child neglect: Evidence from Japan's vital statistics on mortality

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Heterogeneous impacts of local unemployment rates on child neglect: Evidence from Japan's vital statistics on mortality

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Abstract

This study examines the causal impact of the local unemployment rate on child death cases due to unintentional drowning – a common consequence of child neglect – using vital statistics from Japan. We use predicted overall and gender-specific local unemployment rates derived from a shift-share research design, rather than the raw local unemployment rates. Our estimation results reveal that a one-percent increase in the overall local unemployment rate correlates with a 7.13% rise in child death cases due to unintentional drowning. When analyzing gender-specific unemployment rates, we find that only increases in female unemployment rates are associated with an uptick in tragic cases. Heterogeneity analysis shows that the impact of female local unemployment rate is more pronounced in regions characterized by lower socioeconomic status, higher proportions of younger parents, a greater prevalence of single-parent households, and fewer public resources. Furthermore, our findings suggest that younger single parents are particularly susceptible to the mental health impacts of increases in female local unemployment rates.

JEL Classification Numbers: I10, J13, R23
Keywords: child neglect, child death cases, unemployment rate, shift-share research design

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1 Introduction

In many developed regions, where the human capital of children – who will be responsible for the future social economy – is becoming increasingly rare due to population decline, child abuse, with its high risk of damaging this crucial human capital, is one of the most urgent and serious issues that modern society must resolve.[1] Estimates show more than 40,000 children under the age of 18 die annually, with some of these deaths likely attributable to child maltreatment (World Health Organization, 2020). Further, nearly three-quarters of children aged between 2 and 4 regularly suffer from physical and/or psychological violence inflicted by their parents and caregivers (World Health Organization, 2020). These statistics are likely underestimated as maltreatment often occurs behind closed doors in the "home" (Briggs and Hawkins, 1997). Child maltreatment has long-term impacts on the development of affected children, even if they survive maltreatment (Campbell et al., 2016; Currie and Tekin, 2012; Currie and Widom, 2010; Fletcher, 2009; Gilbert et al., 2009; Hughes et al., 2017, 2020; Thornberry et al., 2010; Zielinski, 2009). The annual healthcare costs due to child maltreatment alone are estimated at 748 billion dollars in North America and $581 billion in Europe (Bellis et al., 2019). Therefore, exploring the mechanisms leading to child maltreatment and protecting children from such harm is critical not only for the well-being of individual children but also for the sustainability of our society.

Early detection of child maltreatment victims is crucial for rescuing them before their situations worsen. However, the risk factors behind child maltreatment are wide-ranging and complex,[2] making it difficult for authorities to observe some risk factors, such as parents' characteristics, child personality, and the parent-child relationship. Among these risk factors, local macroeconomic conditions, specifically local unemployment rates that could impact the economic status of the child's family, can serve as indicators for child maltreatment, more easily observed by the authorities. The relationship between local unemployment rates and child maltreatment cases has been extensively analyzed, yielding mixed and inconclusive results. Some studies found that an increase in local unemployment rates worsen child maltreatment (Brown and De Cao, 2020; Frioux et al., 2014; Hsin et al., 2018; Oikawa et al., 2022; Schneider et al., 2017; Seiglie, 2004; Yasumi and Kageyama, 2009), while Raissian (2015) found that higher local unemployment rates correlate with a decrease in the number of maltreatment cases in New York State. However, a few studies have obtained

[1]An estimate reveals fertility rates will be below replacement level in over 95% of the world's countries and territories by 2100 (Bhattacharjee et al., 2024).

[2]Stith et al. (2009) reviews the risk factors behind child maltreatment.

mixed and inconclusive findings (Berger et al., 2011; Bitler and Zavodny, 2004; Lindo et al., 2018; Nguyen, 2013; Paxson and Waldfogel, 1999, 2002). Thus, more studies are required to clarify the relationship between local macroeconomic conditions and the prevalence of child maltreatment.

One reason for the mixed results is that few studies have conclusively identified the causal effect of local unemployment rates on the prevalence of child maltreatment (Brown and De Cao, 2020; Lindo et al., 2018; Oikawa et al., 2022). A deterioration of local macroeconomic conditions would constitute a purely exogenous negative shock to the socioeconomic status of households only if it is solely driven by the demand side of the local labor market. However, local macroeconomic conditions may also reflect individual choices on the supply side of the local labor market, introducing potential estimation bias.[3] Additionally, child maltreatment cases tend to be underreported, and attention from residents and authorities towards children could increase during periods of rising unemployment, further complicating accurate estimation.[4]

Another reason could be the heterogeneity of the impacts resulting from various sources. Previous studies have examined the effects of gender-specific local macroeconomic conditions (e.g., Lindo et al., 2018; Paxson and Waldfogel, 1999, 2002). For example, Lindo et al. (2018) found that an increase in the predicted employment rate for males decreases the maltreatment rate, whereas for females, it increases the maltreatment rate. Further, Brown and De Cao (2020) show that the effect of the local unemployment rate on child neglect is smaller in regions with longer extensions of unemployment benefits, suggesting the importance of safety nets in preventing child maltreatment.

This study examines the causal impact of local unemployment rates on child death cases due to unintentional drowning, a proxy for neglect victims, using vital statistics from Japan. Instead of raw local unemployment rates, we used the predicted local unemployment rates based on a shift-share research design. Gender-specific predicted unemployment rates were utilized to explore whether the unemployment status of fathers and mothers differentially impacts child maltreatment victims. Additionally, we examined regional socioeconomic status

[3]For example, we must consider a potential scenario of endogeneity bias stemming from the supply side, where some parents working long hours may choose to voluntarily quit their jobs and seek new ones to allocate more time on non-work activities, including childcare. In such cases, increased parental time spent with children could enhance parent-child relationships, potentially reducing the incidence of child maltreatment. Consequently, the impact of deteriorating local macroeconomic conditions on maltreated children may be underestimated owing to the downward effects of endogenous decisions in the supply side of the local labor market.

[4]For instance, an increase in the unemployment rate may lead to more people staying at home during the day, increasing the likelihood of observing maltreated children in their vicinity.

to explore heterogeneous impacts of local unemployment rates. Analyzing these variations could elucidate the mechanisms underlying the causal relationship between local unemployment rates and child maltreatment victims, potentially informing effective interventions by authorities to save children.

Our findings can be summarized as follows. A one-percent increase in the local overall unemployment rate is associated with a 7.13% rise in child death cases due to unintentional drowning, significant at the 5% level. Analysis using gender-specific unemployment rates revealed that only increases in female unemployment rates correlate with higher child death cases due to unintentional drowning. Moreover, the impact of female unemployment rates on child death cases varies significantly across regions with differing socioeconomic statuses, including education, income, age, household structures, and access to public services. Our results suggest the necessity of allocating additional resources to regions with lower socioeconomic statuses to prevent the adverse effects of local female unemployment rates on child safety. These heterogeneous impacts may offer insights into the varying findings on the relationship between local macroeconomic conditions and child maltreatment. Further detailed analysis of these heterogeneous impacts is essential for a deeper understanding of the causal link between local macroeconomic conditions and child maltreatment.

This paper also contributes to the literature on the impact of local macroeconomic conditions on child health. Many studies have analyzed this impact, but the results are mixed and inconclusive.[5] This is not surprising, given the various channels through which macroeconomic conditions can influence child health. For example, an economic downturn may improve pregnant women's health-related behaviors, such as smoking and drinking, thereby improving infant health (e.g., Dehejia and Lleras-Muney, 2004). Conversely, an aggregate negative economic shock can lead to a decline in household income and job loss, potentially deteriorating the mental health of household members, including children. The policy implications of these findings depend on the specific mechanisms involved, necessitating further exploration. This paper focuses on child deaths related to a specific channel – child neglect – and suggests that child neglect could be a pathway through which macroeconomic conditions affect child health. Examining specific health outcomes, such as death cases by causes, is beneficial in exploring the mechanisms behind the causality. Understanding these

[5] Some studies have found a deterioration in economic conditions can be beneficial for child health (e.g., Akesaka and Kikuchi, 2024; Dehejia and Lleras-Muney, 2004; Kim et al., 2021; Lindo, 2015; Stevens et al., 2015; van den Berg et al., 2020), while others have found that worsening economic conditions adversely affect child health (e.g., Cotti and Simon, 2018; Currie and Tekin, 2015; De Cao et al., 2022; Gassman-Pines et al., 2014; Golberstein et al., 2019). In addition, Page et al. (2019) found differing impacts of state unemployment rates on child health between males and females.

mechanisms can help policymakers develop strategies to protect children.

The remainder of this paper is structured as follows. Section 2 introduces institutional background on child maltreatment and unemployment in Japan; Section 3 describes the identification strategy; Section 4 presents the data; Section 5 summarizes the results and discusses the mechanism behind the results; and Section 6 concludes.

2 Institutional Background

2.1 Child maltreatment in Japan

Child maltreatment is an urgent social issue in Japan. The number of child maltreatment cases reported to and/or handled by authorities has rapidly increased in recent decades, rising 22-fold from 1998 to 2018 (Figure 1). In response to this alarming trend, the Child Abuse Prevention Act was enacted in November 2000 to address the growing problem (Kadonaga and Fraser, 2015). The act defined four types of child maltreatment for the first time: physical abuse, sexual abuse, psychological abuse, and neglect.[6] Under Article 6 of the act, individuals who observe child mistreatment are required to promptly report it to the authorities (notification obligation). The act was revised in October 2004 to expand the definitions of child maltreatment and the scope of the notification obligation. The revised act classified leaving children maltreated by other household members as neglect and defined exposure to domestic violence as a form of psychological abuse. It also expanded the notification obligation to include children who appear to have suffered maltreatment. Further revisions to the act have been made since 2004 to continue addressing this critical issue.[7]

While there is little doubt regarding the increase in child maltreatment in Japan, the reported cases may not accurately reflect the true number of victims, potentially misleading the actual trends of child maltreatment. Previous studies argue that the official records may seriously underestimate the actual number of child maltreatment cases (e.g., Swahn et al., 2006). In Japan, Child Guidance Centers, which are authorities tasked with preventing child maltreatment, have faced labor shortages (Mainichi Shimbun, 2019), potentially leading to an undercounting of child maltreatment prevalence. Additionally, increased social awareness of child maltreatment could contribute to the increase in reported cases (Kadonaga and Fraser,

[6] Article 2 of the act provides the definition of child maltreatment (https://www.japaneselawtranslation.go.jp/ja/laws/view/4033)(accessed on April 1, 2024).

[7] Section 7 of the report by the Children and Families Agency, Government of Japan provides the summary of the revisions (https://www.cfa.go.jp/councils/shingikai/gyakutai_boushi/hogojirei/19-houkoku)(in Japanese)(accessed on April 1, 2024).

2015). The definition of psychological abuse was expanded in 2004, which may also increase reported cases. If these factors are at play, the increase in reported child maltreatment cases may not reflect a true rise in actual cases.

This study uses child death cases related to child maltreatment as a proxy for the actual number of victims instead of relying on reported cases. In the worst-case scenario, child maltreatment results in a child's death. We focused on child death cases caused by unintentional drowning, a common cause of child death related to neglect due to inadequate supervision by caregivers (Damashek et al., 2014). Indeed, an increase in the local unemployment rate, a known risk factor for neglect, has been shown to be correlated with a rise in both reported neglect cases and child deaths caused by unintentional drowning in Japan (Oikawa et al., 2022).

2.2 Unemployment rate in Japan

This subsection briefly shows the trend of the unemployment rate in Japan over recent decades. Figure 2 shows the monthly-level unemployment rate in Japan and the exchange rate from January 1990 (1990m1) to December 2019 (2019m12). Over the past three decades, Japan experienced two significant peaks in the unemployment rate. The first peak occurred in the early 2000s during the "lost decade," with the unemployment rate reaching a maximum of 5.5% in June 2002, August 2002, and April 2003. Following April 2003, the unemployment rate gradually declined. However, another peak emerged from the late 2000s to the early 2010s during the Great Recession, with the unemployment rate again reaching 5.5% in July 2009 before beginning a downward trend.

During the Great Recession, an appreciation of Japan's currency was observed. Export-oriented manufacturing firms, which experienced a decline in sales due to the currency appreciation, reduced their number of non-regular workers (Yokoyama et al., 2021). Consequently, the national unemployment rate for the manufacturing industry likely increased. Further, workers in prefectures with a higher proportion of manufacturing firms were at a greater risk of being laid off due to the adverse macroeconomic shock, whereas those in prefectures with a higher proportion of service industry firms were less affected. Such an exogenous shock is likely to have heterogeneous impacts on workers across different industries, given the varied industrial structures across prefectures. Therefore, the effects of the national-level shock would be experienced heterogeneously across prefectures.

3 Identification Strategy

One can consider simply regressing child death cases on unemployment rate. However, the unemployment rate itself is endogenous because it captures supply-side responses in the local labor market in addition to the demand-side responses that we wish to capture. Specifically, on the supply-side, workers may voluntarily choose to stay unemployed to seek better job opportunities. This behavior can promote participation in child-rearing, resulting in fewer child death cases. Due to this endogeneity bias, the causal effects of unemployment rate on child death cases are likely to be underestimated.

To mitigate this endogeneity issue, we leverage the Bartik variable, which exploits exogenous sources of variation in the unemployment rate driven solely by demand-side factors (Bartik, 1991). The Bartik variable is based on a shift-share research design. In our context, *shift* refers to the national-level unemployment rate, which is considered exogenous because it is independent of workers' decisions in the local labor market. However, the impacts vary depending on the industrial structures in each region. *Share* reflects this fact, referring to the proportion of workers in a specific industry relative to the total workforce in each region.

Namely, the Bartik unemployment rate $\widehat{UnempRate}_{pt}$ is constructed by

$$\widehat{UnempRate}_{pt} = \sum_{j=1}^{J} \underbrace{w_{jp}}_{\text{share}} \underbrace{UnempRate_{jt}}_{\text{shift}}, \tag{1}$$

where p, t, j are the indices for prefecture, year, and industry, respectively. The weight w_{jp}, corresponding to *share* is the proportion of employed persons in industry j in prefecture p as of 2005, which satisfies $\sum_{j=1}^{J} w_{jp} = 1$ for each p. The variable $UnempRate_{jt}$, corresponding to *shift* is the national-level unemployment rate of industry j in year t.

Accordingly, we estimate the following model[8]:

$$Death_{pt} = \beta_0 + \beta_1 \log\left(\widehat{UnempRate}_{pt}\right) + x'_{pt}\gamma + \phi_p + \rho_t + u_{pt}, \tag{2}$$

where the dependent variable $Death_{pt}$ denotes the number of child death cases per 100,000 children, defined as individuals aged 18 or younger. The main independent variable $\log\left(\widehat{UnempRate}_{pt}\right)$ is the natural logarithm of the Bartik unemployment rate. The vector

[8] While most studies in economics often use the Bartik variable as an instrumental variable for the endogenous local macroeconomic conditions (e.g., Brown and De Cao, 2020; Oikawa et al., 2022), we directly use it as an exogenous independent variable. This approach is taken because it is difficult to obtain prefecture-level data on gender-specific unemployment rates.

x_{pt} represents a set of control variables, including the total population, number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), number of employees at Child Guidance Centers (CGC) per 100,000 children, financial capability indicator, and a dummy variable for Iwate and Miyagi in 2011.[9] Parameters ϕ_p, ρ_t denote prefecture fixed effects and year fixed effects, respectively, and u_{pt} is an error term.

Moreover, we consider a model with gender-specific unemployment rates instead of the overall unemployment rate, as fathers' and mothers' unemployment statuses have different effects on child maltreatment (Lindo et al., 2018). This regression model is given by

$$\begin{aligned} Death_{pt} =& \beta_0 + \beta_{1,m} \log\left(\widehat{UnempRate}_{pt,m}\right) + \beta_{1,f} \log\left(\widehat{UnempRate}_{pt,f}\right) \\ & + x'_{pt}\gamma + \phi_p + \rho_t + u_{pt}, \end{aligned} \tag{3}$$

where $\log\left(\widehat{UnempRate}_{pt,g}\right)$ is the natural logarithm of the gender-specific Bartik unemployment rate, with $g = m$ for male whereas $g = f$ for female. These variables are constructed in the same manner as in the initial equation (1), using male and female counterparts for *share* and *shift* in the Bartik variable.

In estimation, we use weighted least squares (WLS) with sampling weight. This approach is necessary because ordinary least squares (OLS) cannot account for the fact that our main independent variables are prefecture-level aggregate variables. The weights are defined by the population aged 0-18 in each prefecture in the baseline year of 2005. Standard errors are clustered at the prefecture-level, where the unemployment rate is observed.

4 Data

Our dataset comprises prefecture-year level longitudinal data in Japan for the period from 2005-2018 periods.[10][11]

[9] These prefectures were severely affected by the Great East Japan Earthquake in 2011, which likely caused an unnatural increase in the number of child death cases. For the reasons why we exclude Fukushima prefecture from the analysis, please refer to the next section on pages 9-10.

[10] For data sources of control variables and variables in the heterogeneity analysis, please refer to Appendix A.

[11] As described in Section 2, one of the major amendments of the Child Abuse Prevention Act was made in 2004. Therefore, the starting year for the sample periods is set to 2005, when the first Census after the revision was available.

4.1 Child Death

The dependent variable, the number of child death cases, is constructed using the Death Form of the Vital Statistics Survey (DFVS) provided by the Minstry of Health, Labour and Welfare (MHLW). The DFVS is a comprehensive survey covering all death cases of residents in Japan. Using the International Classification of Diseases (ICD-10), we count the number of child deaths by the following three causes: "unintentional drowning" (W65-W73), "external causes other than unintentional drowning" (external causes are calculated by V01-Y98), and "internal causes" (A00-R99) (Yamaoka et al., 2018). We focus on unintentional drowning because unemployment rate is reported to be a risk factor for child maltreatment, which can result in child death, especially due to unintentional drowning (Oikawa et al., 2022). Moreover, we construct the other two variables as placebo checks, as these death cases are likely to be irrelevant to child neglect.

4.2 Unemployment Rate

The unemployment rates are constructed as Bartik variables. Here, we describe the data sources for the *share* and *shift* components of the Bartik variable expressed in Equation (1). First, the data for the *share* component in the Bartik variable is sourced from 2005 Census provided by Ministry of Internal Affairs and Communications (MIAC). We calculate the proportion of workers in each industry in each prefecture, fixing these proportions in the baseline year 2005 for each prefecture.

Conversely, the data for the *shift* component in the Bartik variable is obtained from the Labour Force Survey provided by the MIAC. We collect data on the number of unemployed and employed persons in each industry in each year. Then, for each industry and year, we calculate the national-level unemployment rate by dividing the number of unemployed persons by the total number of unemployed and employed persons.

The industries used for constructing the Bartik variables consist of the following 15 classifications: (1) agriculture and fishery, (2) construction, (3) manufacturing, (4) electricity, gas, heat supply and water, (5) information and communications, (6) transport and postal services, (7) wholesale and retail trade, (8) finance and insurance, (9) real estate and goods rental and leasing, (10) accommodations, eating and drinking services, (11) medical, healthcare and welfare, (12) education, learning support, (13) compound services, (14) services (not elsewhere classified) and (15) government, except elsewhere classified.

4.3 Sample Restriction

We exclude Fukushima prefecture from the sample due to the prolonged evacuation of its residents following the Fukushima Daiichi nuclear power plant accident caused by the Great East Japan Earthquake in 2011. Moreover, when counting the number of child death cases, we restrict the sample to children from households where the primary work status is categorized as self-employed, employed, or unemployed. Specifically, we exclude farming, unknown, and other work types, as these are considered less susceptible to fluctuations in the unemployment rate.

4.4 Descriptive Statistics

Table 1 reports summary statistics for the variables used in our study. For the outcome variables of child death cases, the mean value of unintentional drowning is 0.447 per 100,000 children. Additionally, the mean value of external causes other than unintentional drowning is higher at 3.98 per 100,000 children, as this variable captures child deaths due to various factors such as traffic accidents. Moreover, the mean value of internal causes is the highest at 12.8 per 100,000 children, reflecting cases where children are likely to suffer from diseases, leading to death.

For our main independent variable, the Bartik unemployment rate, the mean value is 2.1, with a minimum of 1.3 and a maximum of 3.2 for the overall unemployment rate. Similar tendencies are observed for gender-specific unemployment rates, though their distributions may differ, as described below. Summary statistics for other control variables and variables used in the heterogeneity analysis are also reported.

We plot the time trends of the overall Baritk unemployment rate in Figure 3, observing sufficient variation across prefectures in each year. Moreover, Figure 4 displays the time trends for gender-specific Bartik unemployment rates, indicating similar chronological movements, but distinct patterns between male and female rates. To further illustrate the differences between these gender-specific unemployment rates, Figure 5 presents their histograms across the whole sample period. The histograms show that male and female unemployment rates do not necessarily overlap, justifying their inclusion in a single model to avoid issues of multicollinearity.

5 Results

5.1 Results for Main Analysis

We first report the results for main analysis. Given that our model uses a level-log specification (i.e., the dependent variable is the raw value of child death cases, while the main independent variable is the logarithm of the Bartik unemployment rate), the coefficient β_1 in model (2) can be interpreted as follows: "the number of child death cases increases by $\beta_1/100$ units when unemployment rate increases by 1%." We further divide $\beta_1/100$ by the mean value of the dependent variable, which represents the percentage change in the dependent variable.

Table 2 shows the results using the overall unemployment rate. Column (1) indicates that higher unemployment leads to an increase in child death cases due to unintentional drowning. Namely, when unemployment rate increases by 1%, the number of child death cases due to unintentional drowning increases by 0.03186 ($= 3.186/100$) cases. Given that the mean value of the dependent variable, the number of child death cases due to unintentional drowning, is 0.447, we can interpret the magnitude of the estimated coefficient as follows: when the unemployment rate increases by 1%, the number of child death cases due to unintentional drowning increases by 7.13% ($= 100 \times 0.03186/0.447$).

Table 3 shows the results using gender-specific unemployment rates.[12] We observe that while male unemployment rate does not significantly affect any type of child death, a higher female unemployment rate leads to more child death cases due to unintentional drowning. According to column (1), when the female unemployment rate increases by 1%, the number of child death cases due to unintentional drowning increases by 6.39%. These results demonstrate that the female unemployment rate, not male unemployment rate, is a predictor for child death due to unintentional drowning.

However, the effects of unemployment rate on child death cases due to unintentional drowning can capture various channels beyond neglect. For instance, unemployment may lead to reduced parental income, resulting in lower investments in the human and health capital of their children, which could lead to child death. To eliminate such alternative paths, including this income channel, we conduct placebo checks by running the same regression models with different dependent variables that are considered irrelevant to neglect: the number of child death cases due to external causes other than unintentional drowning, and those due to internal causes.

[12] Several robustness checks show that our results are robust against different model specifications. For more details, please refer to Appendix B.

Columns (2) and (3) in Table 2 and Table 3 summarize the results for these dependent variables as placebo checks. We do not find statistically significant results for death causes other than unintentional drowning, verifying that the placebo checks work properly.

5.2 Results for Heterogeneity Analysis

We perform heterogeneity analysis to investigate the heterogeneity in the effects of unemployment rate on child death. For the dependent variable in this analysis, we focus exclusively on the number of child death due to unintentional drowning, as this was the only variable found to be affected by the female unemployment rate in the main analysis. The variables for heterogeneity analysis are classified as follows:

- **Monitoring by oneself**: college graduate ratio, household income, mean age
- **Monitoring by others**: single-parent household rate, nuclear family household rate, number of CGC staff

The variables classified under "monitoring by oneself" reflect the extent to which parents monitor their children personally. Namely, highly-educated parents, parents with sufficient incomes, and parents who are not too young are more likely to devote themselves to monitoring their children, resulting in fewer child deaths. In contrast, the variables classified under "monitoring by others" denote the extent to which other people surrounding parents monitor children. For instance, parents with many other household members or those who have access to public services may have more opportunities for their children to be monitored by others, resulting in fewer child deaths.

We show the geographical distribution by prefecture for each variable used in the heterogeneity analyses in Figure 6. Each variable exhibits sufficient variation across prefectures. For the heterogeneity analysis, we estimate model (3) by splitting the whole sample into two subsamples based on the median of each variable described above. Consequently, each subsample consists of 23 (= 46/2) prefectures. Standard errors are robust against prefecture-level clustering, and because the number of clusters is small, they are calculated to address the few clusters problem (Cameron and Miller, 2015).

Table 4 summarizes the results for heterogeneity analysis related to monitoring by oneself. Overall, the effect of the female unemployment rate on child death due to unintentional drowning is more pronounced in regions with lower levels of monitoring. Specifically, the number of child deaths due to unintentional drowning increases by 12.5% with a 1% increase in the female unemployment rate in regions with a lower college graduate ratio, which is about five times larger than in regions with a higher college graduate ratio. Moreover, the number of child deaths due to unintentional drowning increases by 12.75% with a 1% increase in the female unemployment rate in regions with lower median income, which is about six times larger than in regions with higher median income. Furthermore, the number of child deaths due to unintentional drowning increases by 10.01% with a 1% increase in the female unemployment rate in regions with a lower mean age, which is about twice as large as in regions with a higher mean age. These results imply that parental self-monitoring is a crucial buffer in mitigating the adverse effect of the female unemployment rate on child death due to unintentional drowning.

In contrast, Table 5 summarizes the results for heterogeneity analysis related to monitoring by others. Again, the effect of the female unemployment rate on child death due to unintentional drowning is more pronounced in regions with lower levels of monitoring. More concretely, the number of child deaths due to unintentional drowning increases by 7.49% with a 1% increase in the female unemployment rate in regions with a higher single-parent household rate, which is about twice as large as in regions with a lower single-parent household rate. Moreover, the number of child deaths due to unintentional drowning increases by 7.41% with a 1% increase in the female unemployment rate in regions with a higher nuclear family household rate, which is close to but larger than in regions with a lower nuclear family household rate. Furthermore, the number of child deaths due to unintentional drowning increases by 8.33% with a 1% increase in the female unemployment rate in regions with fewer CGC staff, which is about twice as large as in regions with more CGC staff. These results suggest that monitoring by others plays an important role in mitigating the adverse effect of the female unemployment rate on child death due to unintentional drowning.

5.3 Mechanism: parents' mental health

We discuss one possible mechanism to explain why a higher female unemployment rate increases child death cases due to unintentional drowning: parents' stress level, which are a risk factor of child neglect, as found in the meta-analysis of Stith et al. (2009). We examine this mechanism by estimating the following model:

$$
\begin{aligned}
Y_{ipt} = {} & \tilde{\beta}_0 + \tilde{\beta}_{1,m} \log\left(\widehat{UnempRate}_{pt,m}\right) + \tilde{\beta}_{1,f} \log\left(\widehat{UnempRate}_{pt,f}\right) \\
& + x'_{2ipt}\tilde{\gamma} + \tilde{\phi}_p + \tilde{\rho}_t + e_{ipt},
\end{aligned} \tag{4}
$$

where i, t, and p are the indexes of individuals, years, and prefectures, respectively. Here, Y_{ipt} denotes stress-related variables: the Kessler 6-item psychological distress (K6) score, and a dummy variable indicating whether an individual reported feeling stress (Kessler et al., 2002, 2010).[13] The vector x_{2ipt} includes individual characteristics (age dummy variables and the number of household members dummy variables), as well as the prefecture-level variables used in Equation (3).[14] Parameters $\tilde{\phi}_p$ and $\tilde{\rho}_t$ are prefecture and year fixed effects, respectively, and e_{it} is the unobserved error term.

The data used for this analysis come from the Comprehensive Survey of Living Conditions (CSLC). The CSLC is a nationally representative repeated cross-sectional survey conducted by the MHLW every three years. We used the 2007, 2010, 2013, and 2016 CSLC data to ensure consistency with the sample periods of the main dataset.[15] The sample was restricted to individuals aged between 16 and 49 who have children. We conducted subgroup analysis by parents' gender and household type. The model is estimated using WLS with the CSLC sampling weight.

Table 6, summarizing the estimation results of Equation (4), shows that local unemployment rates affected parents' mental health heterogeneously by household type and parents' gender. Among fathers from nuclear families, we observed statistically significant coefficients for male and female unemployment rates, with the signs of the coefficients differing between the two variables: negative estimates for male unemployment rates and positive estimates for female unemployment rates (Column (1) in Panel A). The estimates suggest that a one-percent increase in the male unemployment rate decreases the K6 score by 0.042 points, while a one-percent increase in the female unemployment rate increases the K6 score by 0.045 points.

There could be at least two channels behind the mental health impacts of unemployment rates: an increased unemployment rate causes a decrease in working hours, leading to (1) a reduction in stress due to long working hours (e.g., Sato et al., 2020), and (2) a decline in income, which deteriorates mental health (e.g., Ridley et al., 2020; Sareen et al., 2011). In addition, the mental health impacts could extend to other household members, including

[13]The K6 score generates a score ranging from 0 to 24, with higher scores reflecting greater levels of psychological distress and serious mental illness.

[14]The proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees at CGCs per 100,000 children, the financial capability indicator, and a dummy variable for Iwate and Miyagi in 2011 are included.

[15]The respondents were selected using stratified random sampling across Japan for each survey year. The survey collected data on demographic characteristics, including age, gender, marital status, type of residence, and the prefectures where respondents reside, as well as health-related characteristics.

spouses. Given that males face long working hours,[16] an increase in male unemployment rates might cause an easing of long working hours, leading to mental health improvement. This channel could be more significant than the income decline channel, resulting in the negative health impact of male unemployment rates. On the other hand, increased female unemployment rates might lead to a decline in their spouses' income, potentially resulting in a deterioration of mental health. If the male and female unemployment rates increase by the same amount simultaneously, their impacts could cancel each other out. A similar tendency is observed for self-reported stress (Column (1) in Panel B). Among mothers from nuclear families, we obtained a statistically significant impact of female unemployment rates, implying that a one-percent increase in the female unemployment rate increases their K6 scores by 0.051 points. For mothers, female unemployment rates may affect their mental health through the income decline channel, given that females are less likely to face long working hours.[17]

The group most vulnerable to the increase in the local unemployment rate is younger single parents (Column (3)). Among younger single parents, a one-percent increase in the female unemployment rate raises the K6 score by 0.780 points. If the female unemployment rate increases by its interquartile range among the single parent sample, the K6 score increases by 148% (Magnitude in percentage change in Column (3) of Panel A), which is more than three times larger than that for mothers from nuclear families (Magnitude in percentage change in Column (2) of Panel A). The result is consistent with the findings of the analysis of death cases, showing that the female unemployment rate has a greater impact in areas with younger parents and single parents. Given that almost all single parents are female,[18] an increase in the female unemployment rate may worsen mental health among female single parents, leading to an increased risk of neglect for their children and an increased death caused by neglect in the worst cases. On the other hand, relatively older single parents did not face a change in mental health due to increased female unemployment rates. The mental health of parents residing with grandparents was also not affected by increased unemployment rates.

[16] According to the Labour Force Survey, 13.8% of males worked more than 60 hours per week in 2010.

[17] According to the Labour Force Survey, the proportion of female workers with working hours of 60 or more was 3.1%, and less than one-fourth of the proportion for males in 2010.

[18] In our sample, 96.4% of the younger single parents are female.

6 Conclusion

This study examines the causal impact of local unemployment rates on child death cases due to unintentional drowning – a common consequence of child neglect – using vital statistics from Japan. We employed overall and gender-specific predicted local unemployment rates based on a shift-share research design rather than raw local unemployment rates. The estimation results reveal that a one-percent increase in the overall local unemployment rate increases child death cases due to unintentional drowning by 7.13%. When using gender-specific unemployment rates, only an increase in female unemployment rates leads to a rise in such cases. Heterogeneity analysis shows that the impacts of female local unemployment rates are more pronounced in regions with lower socioeconomic status, higher proportions of younger parents, single parents, and fewer public resources. Furthermore, younger single parents are identified as particularly vulnerable to the mental health impacts of female local unemployment rates.

To alleviate the adverse effects of female unemployment rates on child deaths from unintentional drowning, our findings underscore the importance of allocating more public resources to these vulnerable regions. Local authorities should consider increasing the number of CGC staff if parental and community monitoring are insufficient. Additionally, personal attributes such as socioeconomic status, parental age, and single parenthood can be assessed by local authorities through methods such as resident tax records and family register information. Constructing a database on these risk factors and sharing it with CGCs could facilitate targeted interventions for high-risk children.

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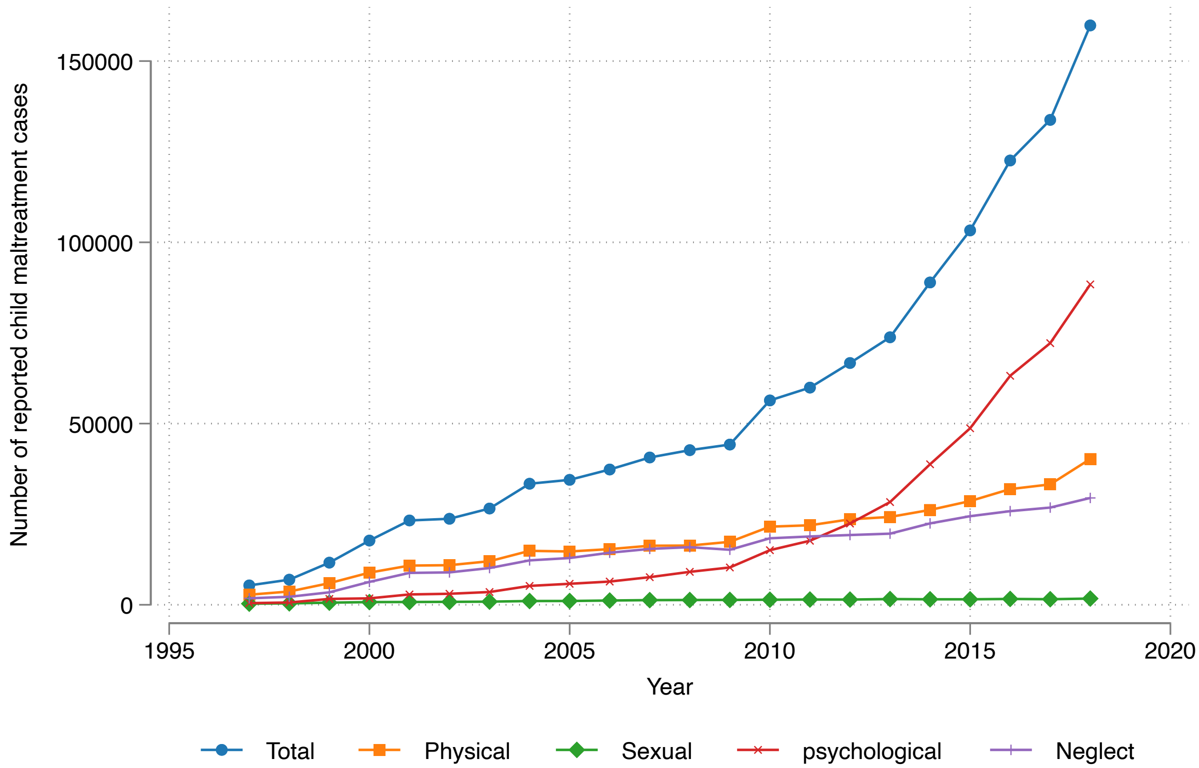


Figure 1: Reported child maltreatment cases

Source: Report on Social Welfare Administration and Services.

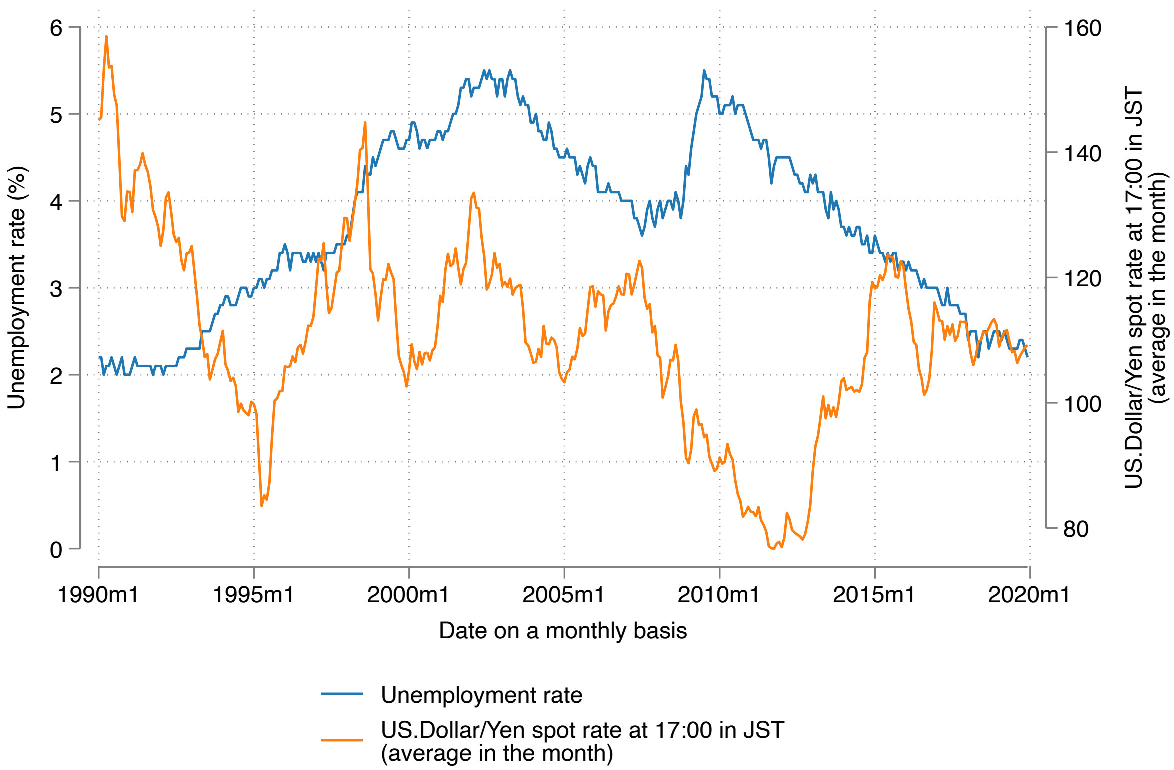


Figure 2: Unemployment rates in Japan and exchange rate

Source: Labour Force Survey and Bank of Japan's main statistical data.

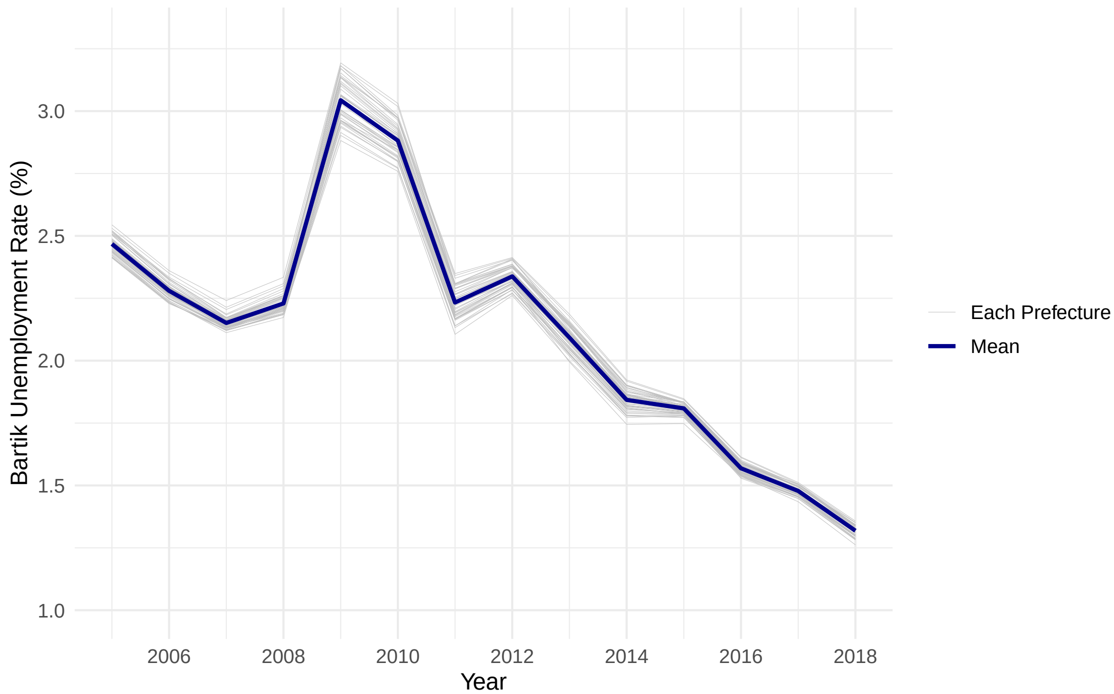


Figure 3: Changes in the Bartik unemployment rate

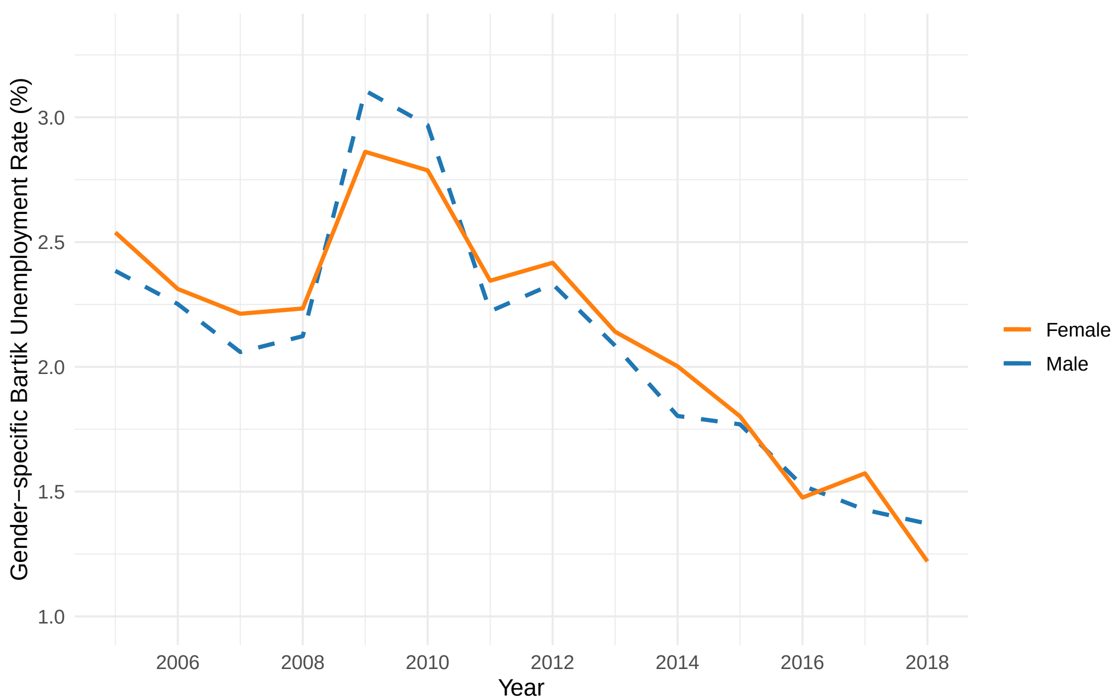


Figure 4: Changes in the mean of gender-specific Bartik unemployment rates

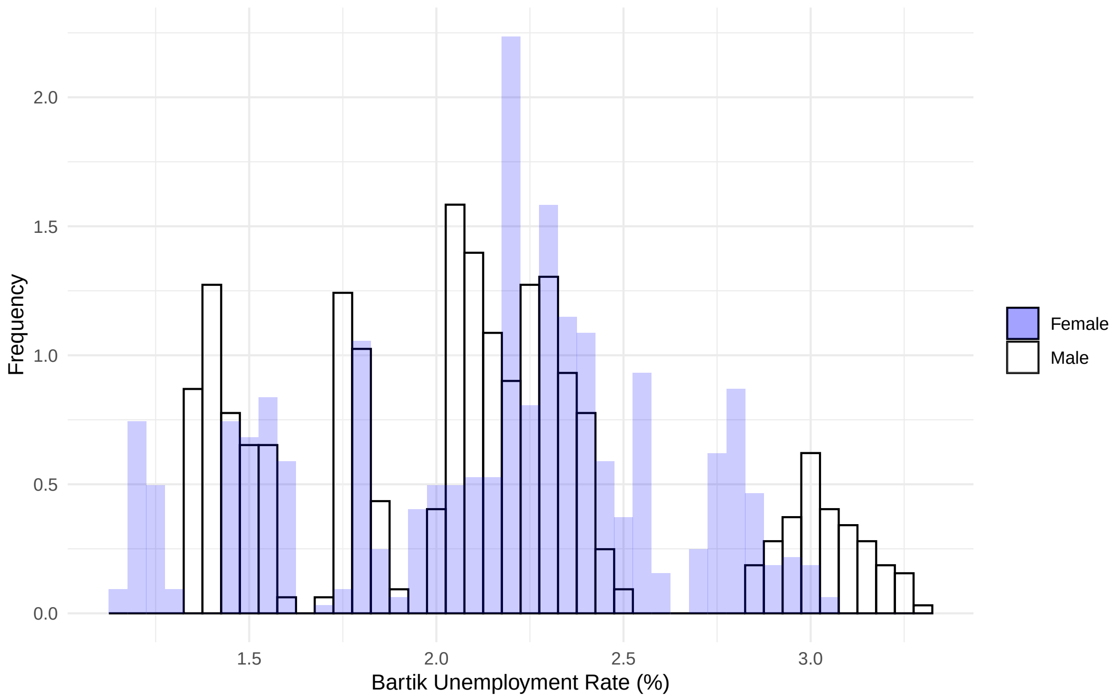
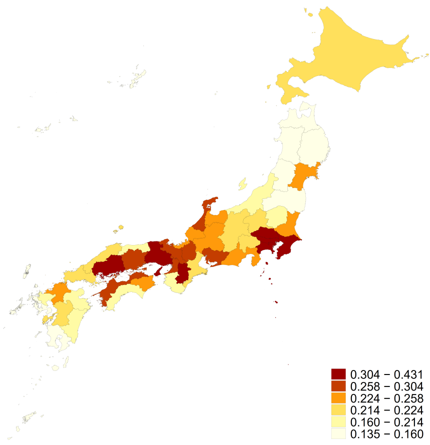
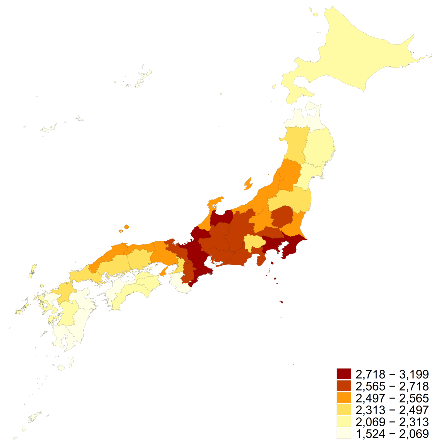


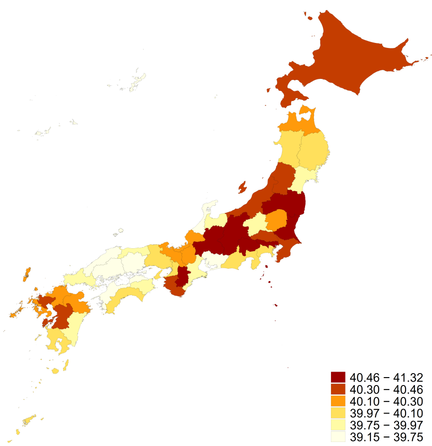
Figure 5: Histogram of gender-specific Bartik unemployment rates



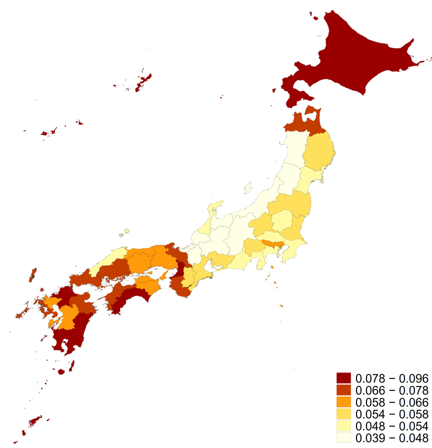
(a) College graduate ratio



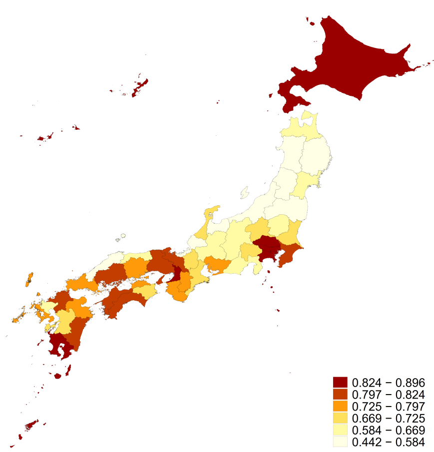
(b) Household income



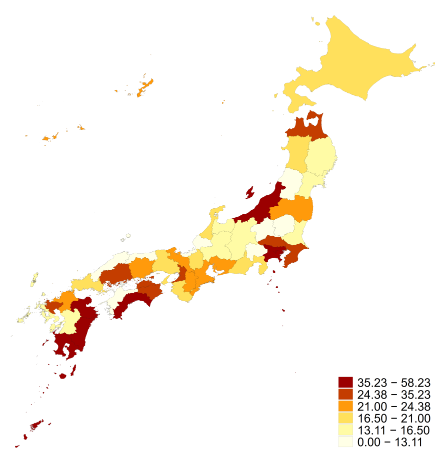
(c) Mean age



(d) Single-parent household rate



(e) Nuclear family household rate



(f) Number of CGC staff

Figure 6: Distribution of variables used in heterogeneity analysis

Table 1: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
Child death outcomes					
Unintentional drowning	644	0.447	0.464	0.000	3.061
External Causes other than Unintentional Drowning	644	3.980	5.885	0.000	128.979
Internal Causes	644	12.798	3.022	3.799	25.850
Bartik unemployment rates					
Overall	644	2.124	0.479	1.262	3.193
Male	644	2.102	0.500	1.331	3.290
Female	644	2.137	0.465	1.166	3.054
Control variables					
Population (Overall)	644	2,727,064.000	2,640,652.000	570,824	13,637,346
Population (0-4 years old)	644	114,513.400	111,964.400	22,719	556,168
Population (5-9 years old)	644	120,777.800	113,236.600	24,333	530,586
Population (10-14 years old)	644	125,657.200	113,963.100	25,655	511,000
Population (15-19 years old)	644	130,935.500	117,600.500	27,087	550,574
Number of CGC staff	644	27.606	15.746	0.000	86.788
Financial capability indicator	644	52.528	18.687	23.265	113.119
Variables used in heterogeneity analysis					
College graduate ratio	644	0.236	0.063	0.135	0.431
Household income	644	2,424.617	323.701	1,524.205	3,198.520
Mean age	644	40.096	0.411	39.152	41.318
Single-parent household rate	644	0.062	0.015	0.039	0.096
Nuclear family household rate	644	0.719	0.110	0.442	0.896
Number of CGC staff	644	27.606	15.746	0.000	86.788

The data are on an annual basis from 2005 to 2018. The unit of observation is the prefecture and year.

Table 2: Effects of overall unemployment rate on child death cases

	(1) Unintentional Drowning	(2) External Causes other than Unintentional Drowning	(3) Internal Causes
Log Unemp Rate	3.186**	-1.052	-6.136
	(1.497)	(4.434)	(11.05)
Number of observations	644	644	644
Overall mean	0.447	3.980	0.133
Magnitude in percentage change	7.13	-0.26	-0.48

The unit of observation is the prefecture and year. The dependent variables are the number of child death cases due to unintentional drowning, external causes other than unintentional drowning, and internal causes per 100,000 children. Standard errors robust against the prefecture (where the unemployment rate is observed) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight.

Table 3: Effects of gender-specific unemployment rates on child death cases

	(1) Unintentional Drowning	(2) External Causes other than Unintentional Drowning	(3) Internal Causes
Male Log Unemp Rate	-0.0071	-2.676	0.9953
	(1.140)	(4.675)	(8.146)
Female Log Unemp Rate	2.853***	1.723	-2.077
	(0.9687)	(3.735)	(6.888)
Number of observations	644	644	644
Overall mean	0.447	3.980	0.133
Magnitude in percentage change			
Male	-0.02	-0.67	0.08
Female	6.39	0.43	-0.16

The unit of observation is the prefecture and year. The dependent variables are the number of child death cases due to unintentional drowning, external causes other than unintentional drowning, and internal causes per 100,000 children. Standard errors robust against the prefecture (where the unemployment rate is observed) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight.

Table 4: Heterogeneous effects: monitoring by oneself

	Whole	Education		Income		Age	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		−	+	−	+	−	+
Log Unemp Male	-0.01	2.38	-1.63	0.09	-0.29	0.58	-1.20
	(0.99)	(0.24)	(0.28)	(0.97)	(0.84)	(0.79)	(0.52)
	[-2.45, 2.22]	[-1.58, 7.53]	[-5.22, 1.44]	[-5.10, 6.01]	[-3.06, 2.92]	[-5.26, 4.99]	[-4.79, 3.27]
	{0.995}	{0.265}	{0.285}	{0.973}	{0.837}	{0.785}	{0.509}
Log Unemp Female	2.85***	5.74**	0.97	6.15**	0.72	4.85***	1.77
	(0.01)	(0.02)	(0.40)	(0.01)	(0.51)	(0.01)	(0.26)
	[0.96, 5.21]	[1.13, 10.71]	[-1.44, 3.56]	[1.62, 10.87]	[-1.56, 3.49]	[1.72, 9.40]	[-1.56, 5.35]
	{0.005}	{0.013}	{0.410}	{0.008}	{0.553}	{0.007}	{0.227}
Number of observations	644	322	322	322	322	322	322
Overall mean	0.447	0.459	0.434	0.483	0.411	0.484	0.409
Magnitude in percentage change							
Male	-0.02	5.18	-3.75	0.19	-0.70	1.20	-2.94
Female	6.39	12.50	2.24	12.75	1.76	10.01	4.33

The unit of observation is the prefecture and year. The dependent variable is the number of child death cases due to unintentional drowning per 100,000 children. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight. (): p-value based on wild bootstrap, []: 95% CI based on wild bootstrap, {}: p-value.

Table 5: Heterogeneous effects: monitoring by others

	Whole	Single Parent		Nuclear Family		CCC Staff	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		−	+	−	+	−	+
Log Unemp Male	-0.01	0.13	-0.71	0.69	-0.93	-0.44	0.49
	(0.99)	(0.93)	(0.66)	(0.84)	(0.44)	(0.88)	(0.69)
	[-2.45, 2.22]	[-3.55, 3.68]	[-5.35, 3.42]	[-6.51, 9.08]	[-4.28, 1.35]	[-6.81, 5.74]	[-2.35, 3.13]
	{0.995}	{0.940}	{0.666}	{0.842}	{0.457}	{0.874}	{0.701}
Log Unemp Female	2.85***	1.24	3.54**	2.97	3.41***	3.67*	2.01*
	(0.01)	(0.43)	(0.02)	(0.26)	(0.01)	(0.08)	(0.10)
	[0.96, 5.21]	[-2.26, 5.10]	[0.70, 8.13]	[-2.52, 8.55]	[1.15, 5.89]	[-0.53, 8.12]	[-0.43, 4.69]
	{0.005}	{0.445}	{0.026}	{0.276}	{0.005}	{0.089}	{0.104}
Number of observations	644	322	322	322	322	322	322
Overall mean	0.447	0.420	0.473	0.433	0.460	0.440	0.453
Magnitude in percentage change							
Male	-0.02	0.30	-1.49	1.59	-2.03	-0.99	1.08
Female	6.39	2.95	7.49	6.85	7.41	8.33	4.44

The unit of observation is the prefecture and year. The dependent variable is the number of child death cases due to unintentional drowning per 100,000 children. Standard errors robust against the prefecture (where the treatment happens) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight. (): p-value based on wild bootstrap, []: 95% CI based on wild bootstrap, {}: p-value.

Table 6: Impacts on parents' mental health

	Nuclear family		Single parent		Three generations	
	(1)	(2)	(3)	(4)	(5)	(6)
	Father	Mother	Age 16-25	Age 26-49	Father	Mother
A. K6						
Log Unemp Male	-4.366***	-1.114	1.198	11.170	-6.298	1.644
	(1.550)	(1.723)	(46.295)	(7.919)	(5.672)	(2.971)
Log Unemp Female	4.690**	5.122**	78.028**	-12.118	3.325	-3.832
	(2.136)	(2.353)	(30.665)	(8.292)	(4.259)	(3.129)
Number of observations	123909	138404	281	12188	31752	42500
Overall mean	2.983	3.562	5.437	5.263	2.939	3.682
Magnitude in percentage change						
Male	-50.29	-10.75	1.67	17.42	-74.03	15.45
Female	42.13	38.87	148.00	-28.68	28.15	-26.14
B. Self-reported stress						
Log Unemp Male	-0.747***	0.139	-6.336	0.228	-0.262	0.339
	(0.180)	(0.193)	(5.699)	(0.598)	(0.495)	(0.431)
Log Unemp Female	0.723***	0.292	0.140	-0.808	0.288	0.402
	(0.173)	(0.217)	(4.020)	(0.666)	(0.469)	(0.410)
Number of observations	126590	141187	285	12609	32850	43925
Overall mean	0.519	0.621	0.717	0.716	0.484	0.604
Magnitude in percentage change						
Male	-49.46	7.67	-67.05	2.62	-18.73	19.42
Female	37.34	12.72	2.02	-14.06	14.80	16.74

We used the 2007, 2010, 2013, and 2016 Comprehensive Survey of Living Conditions. The unit of observation is the individual and year. We restricted the sample to individuals aged between 16 and 49 who have children. The dependent variables are the stress-related variables: the K6 score, and the dummy variable indicating whether an individual reported feeling stress. Standard errors robust against the prefecture (where an individual resides) level clustering are shown between parentheses. All specifications include the age dummy variables, the number of household members dummy variable, the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture (where an individual resides) fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight.

References

Akesaka, Mika and Nobuyoshi Kikuchi, "The effects of gender-specific local labor demand on birth and later outcomes," *Labour Economics*, oct 2024, *90*, 102546.

Bartik, Timothy J., *Who Benefits from State and Local Economic Development Policies?*, Vol. 68 1991.

Bellis, Mark A., Karen Hughes, Kat Ford, Gabriela Ramos Rodriguez, Dinesh Sethi, and Jonathon Passmore, "Life course health consequences and associated annual costs of adverse childhood experiences across Europe and North America: a systematic review and meta-analysis," *The Lancet Public Health*, 2019, *4* (10), e517–e528.

Berger, Rachel P., Janet B. Fromkin, Haley Stutz, Kathi Makoroff, Philip V. Scribano, Kenneth Feldman, Li Chuan Tu, and Anthony Fabio, "Abusive head trauma during a time of increased unemployment: A multicenter analysis," *Pediatrics*, 2011, *128* (4), 637–643.

Bhattacharjee, Natalia V, Austin E Schumacher, Amirali Aali, Yohannes Habtegiorgis Abate, Rouzbeh Abbasgholizadeh, Mohammadreza Abbasian, Mohsen Abbasi-Kangevari, Hedayat Abbastabar, Samar Abd ElHafeez, Sherief Abd-Elsalam, and Others, "Global fertility in 204 countries and territories, 1950–2021, with forecasts to 2100: a comprehensive demographic analysis for the Global Burden of Disease Study 2021," *The Lancet*, mar 2024, pp. 1–59.

Bitler, Marianne P. and Madeline Zavodny, "Child Maltreatment, Abortion Availability, and Economic Conditions," *Review of Economics of the Household*, 2004, *2* (2), 119–141.

Briggs, Freda and Russell Hawkins, *Child protection : a guide for teachers and child care professionals* 1997.

Brown, Dan and Elisabetta De Cao, "Child maltreatment, unemployment, and safety nets," 2020.

Cameron, A Colin and Douglas L Miller, "A practitioner's guide to cluster-robust inference," *Journal of Human Resources*, 2015, *50* (2), 317–372.

Campbell, Jennifer A., Rebekah J. Walker, and Leonard E. Egede, "Associations Between Adverse Childhood Experiences, High-Risk Behaviors, and Morbidity in Adulthood," *American Journal of Preventive Medicine*, mar 2016, *50* (3), 344–352.

Cotti, Chad and David Simon, "the Impact of Stock Market Fluctuations on the Mental and Physical Well-Being of Children," *Economic Inquiry*, 2018, *56* (2), 1007–1027.

Currie, Janet and Cathy Spatz Widom, "Long-term consequences of child abuse and neglect on adult economic well-being," *Child Maltreatment*, 2010, *15* (2), 111–120.

_ **and Erdal Tekin**, "Understanding the cycle: Childhood maltreatment and future crime," *Journal of Human Resources*, 2012, *47* (2), 509–549.

_ **and** _ , "Is there a link between foreclosure and health?," *American Economic Journal: Economic Policy*, 2015, *7* (1), 63–94.

Damashek, Amy, Sabrina Drass, and Barbara L. Bonner, "Child maltreatment fatalities related to inadequate caregiver supervision," *Journal of Interpersonal Violence*, 2014, *29* (11), 1987–2001.

De Cao, Elisabetta, Barry McCormick, and Catia Nicodemo, "Does unemployment worsen babies' health? A tale of siblings, maternal behaviour, and selection: Does unemployment worsen babies' health?," *Journal of Health Economics*, 2022, *83* (January), 102601.

Dehejia, R. and A. Lleras-Muney, "Booms, Busts, and Babies' Health," *The Quarterly Journal of Economics*, aug 2004, *119* (3), 1091–1130.

Fletcher, Jason M., "Childhood mistreatment and adolescent and young adult depression," *Social Science and Medicine*, 2009, *68* (5), 799–806.

Frioux, Sarah, Joanne N. Wood, Oludolapo Fakeye, Xianqun Luan, Russell Localio, and David M. Rubin, "Longitudinal Association of County-Level Economic Indicators and Child Maltreatment Incidents," *Maternal and Child Health Journal*, nov 2014, *18* (9), 2202–2208.

Gassman-Pines, Anna, Elizabeth Oltmans Ananat, and Christina M. Gibson-Davis, "Effects of statewide job losses on adolescent suicide-Related behaviors," *American Journal of Public Health*, 2014, *104* (10), 1964–1970.

Gilbert, Ruth, Cathy Spatz Widom, Kevin Browne, David Fergusson, Elspeth Webb, and Staffan Janson, "Burden and consequences of child maltreatment in high-income countries," *The Lancet*, 2009, *373* (9657), 68–81.

Golberstein, Ezra, Gilbert Gonzales, and Ellen Meara, "How do economic downturns affect the mental health of children? Evidence from the National Health Interview Survey," *Health Economics (United Kingdom)*, 2019, *28* (8), 955–970.

Hsin, Yi Chen, Yu Ching Chang, En Pei Lee, Cheng Hsun Chiu, I. Jun Chou, Shao Hsuan Hsia, Kuang Lin Lin, Jung Lee, Jing Long Huang, Chao Jan Wang, and Han Ping Wu, "Risk factors for child maltreatment by the utilization of medical service and socioeconomic environment in Taiwan," *Medicine (United States)*, 2018, *97* (52), 1–5.

Hughes, Karen, Mark A. Bellis, Katherine A. Hardcastle, Dinesh Sethi, Alexander Butchart, Christopher Mikton, Lisa Jones, and Michael P. Dunne, "The effect of multiple adverse childhood experiences on health: a systematic review and meta-analysis," *The Lancet Public Health*, 2017, *2* (8), e356–e366.

Hughes, Nathan, Michael Ungar, Abigail Fagan, Joseph Murray, Olayinka Atilola, Kitty Nichols, Joana Garcia, and Stuart Kinner, "Health determinants of adolescent criminalisation," *The Lancet Child and Adolescent Health*, 2020, *4* (2), 151–162.

Kadonaga, Tomoko and Mark W. Fraser, "Child maltreatment in Japan," *Journal of Social Work*, 2015, *15* (3), 233–253.

Kessler, Ronald C, Gavin Andrews, Lisa J Colpe, Eva Hiripi, Daniel K Mroczek, S-LT Normand, Ellen E Walters, and Alan M Zaslavsky, "Short screening scales to monitor population prevalences and trends in non-specific psychological distress," *Psychological Medicine*, 2002, *32* (6), 959–976.

_ , Jennifer Greif Green, Michael J Gruber, Nancy A Sampson, Evelyn Bromet, Marius Cuitan, Toshi A Furukawa, Oye Gureje, Hristo Hinkov, Chi-Yi Hu et al., "Screening for serious mental illness in the general population with the K6 screening scale: results from the WHO World Mental Health (WMH) survey initiative," *International Journal of Methods in Psychiatric Research*, 2010, *19* (S1), 4–22.

Kim, Bongkyun, Michael R. Thomsen, Rodolfo M. Nayga, and Anthony Goudie, "The effect of gender-specific labor market conditions on children's weight," *Health Economics Review*, 2021, *11* (1), 1–13.

Lindo, Jason M., "Aggregation and the estimated effects of economic conditions on health," *Journal of Health Economics*, 2015, *40*, 83–96.

_ , Jessamyn Schaller, and Benjamin Hansen, "Caution! Men not at work: Gender-specific labor market conditions and child maltreatment," *Journal of Public Economics*, 2018, *163*, 77–98.

Mainichi Shimbun, "Editorial: Child guidance centers in Japan need more resources to tackle abuse," 2019. https://mainichi.jp/english/articles/20190621/p2a/00m/0dm/003000c.

Nguyen, Loc H., "The relationship between unemployment and child maltreatment: A county-level perspective in California," *Children and Youth Services Review*, 2013, *35* (9), 1543–1555.

Oikawa, Masato, Akira Kawamura, Cheolmin Kang, Zentaro Yamagata, and Haruko Noguchi, "Do macroeconomic shocks in the local labor market lead to child maltreatment and death?: Empirical evidence from Japan," *Child Abuse & Neglect*, 2022, *124*, 105430.

Page, Marianne, Jessamyn Schaller, and David Simon, "The effects of aggregate and gender-specific labor demand shocks on child health," *Journal of Human Resources*, 2019, *54* (1), 37–78.

Paxson, Christina and Jane Waldfogel, "Parental resources and child abuse and neglect," *American Economic Review*, 1999, *89* (2), 239–244.

_ and _ , "Work , Welfare , and Child Maltreatment," *Journal of Labor Economics*, 2002, *20* (3), 435–474.

Raissian, Kerri M., "Does unemployment affect child abuse rates? Evidence from New York State," *Child Abuse and Neglect*, 2015, *48*, 1–12.

Ridley, Matthew, Gautam Rao, Frank Schilbach, and Vikram Patel, "Poverty, depression, and anxiety: Causal evidence and mechanisms," *Science*, 2020, *370* (6522).

Sareen, Jitender, Tracie O. Afifi, Katherine A. McMillan, and Gordon J. G. Asmundson, "Relationship Between Household Income and Mental Disorders," *Archives of General Psychiatry*, 2011, *68* (4), 419.

Sato, Kaori, Sachiko Kuroda, and Hideo Owan, "Mental health effects of long work hours, night and weekend work, and short rest periods," *Social Science and Medicine*, 2020, *246* (December 2019), 112774.

Schneider, William, Jane Waldfogel, and Jeanne Brooks-Gunn, "The Great Recession and risk for child abuse and neglect," *Children and Youth Services Review*, 2017, *72*, 71–81.

Seiglie, Carlos, "Understanding Child Outcomes: An Application to Child Abuse and Neglect," *Review of Economics of the Household*, 2004, *2* (2), 143–160.

Stevens, Ann H., Douglas L Miller, Marianne E Page, and Mateusz Filipski, "The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality," *American Economic Journal: Economic Policy*, nov 2015, *7* (4), 279–311.

Stith, Sandra M., Ting Liu, L. Christopher Davies, Esther L. Boykin, Meagan C. Alder, Jennifer M. Harris, Anurag Som, Mary McPherson, and J. E.M.E.G. Dees, "Risk factors in child maltreatment: A meta-analytic review of the literature," *Aggression and Violent Behavior*, 2009, *14* (1), 13–29.

Swahn, Monica H., Daniel J. Whitaker, Courtney B. Pippen, Rebecca T. Leeb, Linda A. Teplin, Karen M. Abram, and Gary M. McClelland, "Concordance between self-reported maltreatment and court records of abuse or neglect among high-risk youths," *American Journal of Public Health*, 2006, *96* (10), 1849–1853.

Thornberry, Terence P., Kimberly L. Henry, Timothy O. Ireland, and Carolyn A. Smith, "The Causal Impact of Childhood-Limited Maltreatment and Adolescent Maltreatment on Early Adult Adjustment," *Journal of Adolescent Health*, 2010, *46* (4), 359–365.

van den Berg, Gerard J., Alexander Paul, and Steffen Reinhold, "Economic conditions and the health of newborns: Evidence from comprehensive register data," *Labour Economics*, 2020, *63* (October 2019), 101795.

World Health Organization, "Fact sheet for child maltreatment," https://www.who.int/news-room/fact-sheets/detail/child-maltreatment 2020. Accessed on September 23, 2020.

Yamaoka, Yui, Naho Morisaki, Haruko Noguchi, Hideto Takahashi, and Nanako Tamiya, "Comprehensive assessment of risk factors of cause-specific infant deaths in Japan," *Journal of Epidemiology*, 2018, *28* (6), 307–314.

Yasumi, Katsuhiro and Jinsuke Kageyama, "Filicide and fatal abuse in Japan, 1994-2005: Temporal trends and regional distribution," *Journal of Forensic and Legal Medicine*, 2009, *16* (2), 70–75.

Yokoyama, Izumi, Kazuhito Higa, and Daiji Kawaguchi, "Employment Adjustments of Regular and Non-Regular Workers to Exogenous Shocks: Evidence from Exchange-Rate Fluctuation," *Industrial and Labor Relations Review*, mar 2021, *74* (2), 470–510.

Zielinski, David S., "Child maltreatment and adult socioeconomic well-being," *Child Abuse and Neglect*, 2009, *33* (10), 666–678.

Appendix

A Additional Information on Data

Here are the detailed description of the control variables used in the main analysis and the variables for heterogeneity analysis:

A.1 Control Variables

1. Total population and number of children by age group

   We use Population, Demographic and Household Surveys Based on the Basic Resident Ledger provided by the MIAC. The data contain information on both total population and population by five-year age group (0-4, 5-9, 10-14, and 15-19).

2. Number of employees of CGC per 100,000 children

   We use Personnel Management Related to Local Governments provided by the MIAC. We extract information on the number of caseworkers in charge of child welfare laws working in CGCs. This number is divided by the population aged 0-18 and multiplied by 100,000.[19]

3. Financial Capability Indicator

   We use List of Key Financial Indicators for Local Governments provided by the MIAC. Municipality-level data is aggregated at the prefecture-level by averaging municipality-level financial capability indicators.

A.2 Variables for Heterogeneity Analysis

We provide detailed description of the variables used in heterogeneity analysis. Specifically, the variables are classified into the following categories: education, income, age, single-parent household rate, nuclear family household rate, and number of CGC staff.[20]

[19]The population aged 0-18 is calculated by (population aged 0-4) + (population aged 5-9) + (population aged 10-14) + (population aged 15-18), where (population aged 15-18) = $\frac{4}{5}$(population aged 15-19).

[20]The subjects in these variables are restricted to parents who have at least one child aged 0-18 to ensure consistency with the main dataset. Moreover, we set the sample periods as close to 2005 as possible, which marks the beginning of the sample period for the main dataset, to maintain consistency. However, when the sample size is small, we include data from later periods.

1. Education (College Graduate Ratio)

   We use the Comprehensive Survey of Living Conditions (CSLC) (Household Survey) in 2010 provided by the MHLW. The college graduate ratio is calculated by dividing the number of individuals with an undergraduate or graduate degree by the total number of individuals.

2. Income (Median Equivalent Disposable Income)

   We utilize the CSLC (Income Survey) in 2007, 2010, 2013, and 2016, provided by the MHLW. Median of equivalent disposable income is calculated for each prefecture.[21]

3. Age (Average Parental Age)

   We use the CSLC (Household Survey) in 2007 provided by the MHLW. Average of parental age is calculated for each prefecture.

4. Single-Parent Household Rate

   We use Census in 2005 provided by the MIAC. The sample is restricted to households with at least one person aged less than 18. Then, we calculate the rate by dividing the sum of single-mother households and single-father households by the total number of households.

5. Nuclear Family Household Rate

   We also use Census in 2005 provided by the MIAC. The sample is restricted to households with at least one person aged less than 18. We calculate the rate by dividing the number of nuclear family households by the total number of households.

6. Number of Child Guidance Center Staff

   We use the same definition as the control variable "the number of employees of CGC per 100,000 children" in 2005.

These variables provide comprehensive coverage of demographic, socioeconomic, and institutional factors that may influence the relationship between unemployment rates and child death cases due to unintentional drowning in Japan.

[21] Equivalent disposable income is calculated by dividing the household's income by the square root of the number of household members. This adjustment is necessary for the effect of household's size on income. The detailed calculation process for equivalent disposable income is the following document: https://www.mhlw.go.jp/toukei/list/dl/20-21a-01.pdf(in Japanese)(accessed on January 25, 2024).

B Robustness Checks

We conduct four robustness checks for the main analysis, focusing on the model with gender-specific unemployment rates, which serves as the benchmark model in our study.

First, we estimate the model using OLS instead of WLS. WLS estimation was initially used to address the concern that our main independent variable, the unemployment rate, is aggregated at the prefecture-level. If the effects are robust, the change in estimation method should not significantly alter our results. Table B.1 shows that an increase in female unemployment rate continues to be associated with an increase in child death cases due to unintentional drowning, even when OLS estimation is used.

Second, we include urban-year fixed effects. Although we attempt to mitigate endogeneity bias through the Bartik variable and various control variables, our model may still be affected by endogeneity bias arising from time-variant regional characteristics. To address this issue, we include urban-year fixed effects, which are interaction terms between urban and year dummy variables.[22] Table B.2 demonstrates that our results remain robust with the inclusion of urban-year fixed effects.

Third, we incorporate prefecture linear time trends. This consideration is similar to the second robustness check. Namely, we include prefecture linear time trends to eliminate endogeneity bias arising from linear time trends in each prefecture. Table B.3 shows that our results are robust to this adjustment.

Finally, we change the specification of unemployment rate. Specifically, we change it from a logged variable to the level variable. Table B.4 indicates that our results are qualitatively robust to this change in the specification of unemployment rate.

[22]The urban prefectures are defined as those included in three metropolitan areas of Japan. Specifically, the urban dummy variable is equal to 1 if the prefecture is Tokyo, Saitama, Kanagawa, Chiba, Aichi, Gifu, Mie, Osaka, Hyogo, Kyoto, or Nara; 0 otherwise.

Table B.1: Robustness check (OLS estimation)

	(1) Unintentional Drowning	(2) External Causes other than Unintentional Drowning	(3) Internal Causes
Male Log Unemp Rate	0.8784	-1.884	-2.291
	(1.853)	(6.182)	(10.03)
Female Log Unemp Rate	4.481**	0.4509	1.632
	(1.667)	(5.271)	(10.11)
Number of observations	644	644	644
Overall mean	0.447	3.980	0.133
Magnitude in percentage change			
Male	1.97	-0.47	-0.18
Female	10.03	0.11	0.13

The unit of observation is the prefecture and year. The dependent variables are the number of child death cases due to unintentional drowning, external causes other than unintentional drowning, and internal causes per 100,000 children. Standard errors robust against the prefecture (where the unemployment rate is observed) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using OLS instead of WLS.

Table B.2: Robustness check (urban-year fixed effects)

	(1) Unintentional Drowning	(2) External Causes other than Unintentional Drowning	(3) Internal Causes
Male Log Unemp Rate	-0.2986	-0.4046	3.185
	(1.481)	(5.452)	(7.619)
Female Log Unemp Rate	3.676***	-3.362	-3.502
	(1.135)	(4.127)	(7.211)
Number of observations	644	644	644
Overall mean	0.447	3.980	0.133
Magnitude in percentage change			
Male	-0.67	-0.10	0.25
Female	8.23	-0.84	-0.27

The unit of observation is the prefecture and year. The dependent variables are the number of child death cases due to unintentional drowning, external causes other than unintentional drowning, and internal causes per 100,000 children. Standard errors robust against the prefecture (where the unemployment rate is observed) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight. We additionally include urban-year fixed effects in the models.

Table B.3: Robustness check (prefecture linear time trends)

	(1) Unintentional Drowning	(2) External Causes other than Unintentional Drowning	(3) Internal Causes
Male Log Unemp Rate	0.3867	-3.208	9.684
	(1.367)	(5.364)	(8.623)
Female Log Unemp Rate	2.640**	1.040	5.200
	(1.186)	(3.954)	(7.359)
Number of observations	644	644	644
Overall mean	0.447	3.980	0.133
Magnitude in percentage change			
Male	0.87	-0.81	0.76
Female	5.91	0.26	0.41

The unit of observation is the prefecture and year. The dependent variables are the number of child death cases due to unintentional drowning, external causes other than unintentional drowning, and internal causes per 100,000 children. Standard errors robust against the prefecture (where the unemployment rate is observed) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. To interpret the magnitude of the estimated coefficients, we also reported the percentage change of the coefficients compared to the overall mean in the event that the unemployment rates increased by an interquartile range (Magnitude in percentage change). Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight. We additionally include prefecture linear time trends in the models.

Table B.4: Robustness check (log to level)

	(1) Unintentional Drowning	(2) External Causes other than Unintentional Drowning	(3) Internal Causes
Male Unemp Rate	-0.1992	-0.6007	1.094
	(0.4246)	(2.146)	(3.318)
Female Unemp Rate	1.206**	0.4377	-1.364
	(0.4816)	(2.102)	(2.911)
Number of observations	644	644	644
Overall mean	0.447	3.980	0.133

The unit of observation is the prefecture and year. The dependent variables are the number of child death cases due to unintentional drowning, external causes other than unintentional drowning, and internal causes per 100,000 children. Standard errors robust against the prefecture (where the unemployment rate is observed) level clustering are shown in parentheses. All specifications include the proportion of the total population, the number of children by five-year age group (0-4, 5-9, 10-14, and 15-19), the number of employees of child guidance centers per 100,000 children, the financial capability indicator, the dummy variable of Iwate and Miyagi in 2011, the year fixed effects, and the prefecture fixed effects. Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The models are estimated using the WLS with the sampling weight. We use the usual gender-specific local unemployment rates instead of taking their logarithms.