Essays on Economics of Man-Made Disasters

by

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Daniel Yi Xu

Dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy
in the Department of Economics
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ABSTRACT

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Abstract

The severity of man-made disasters has been increasing recently and is expected to further increase with climate change. For example, the number of conflicts and their associated fatalities have risen by 105% and 286% since 2010, respectively. With the internet and technological advancement, disasters significantly affect individual welfare both directly and indirectly. I study how the end of a man-made disaster affects labor market outcomes over time and how disasters affect risk preferences in the long run and time use in the short run. In Chapter 2, I study the causal impact of peace on labor market outcomes using the sudden and unexpected end of the Aceh Insurgency in Indonesia in a difference-in-differences framework. In Chapter 3, the intergenerational effects of early life exposure to the Korean War on risk preferences are examined in a difference-in-differences-type model with both structural and reduced-form estimation methods. In Chapter 4, I take the 2014 *Sewol* ferry disaster as a natural experiment to examine the causal effects of an exogenous psychological shock on time use.

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Chapter 1

Introduction

The severity of man-made disasters has been increasing recently and is expected to further increase with climate change. For example, the number of conflicts and their associated fatalities have risen by 105% and 286% since 2010, respectively. With the internet and technological advancement, disasters significantly affect individual welfare both directly and indirectly.

Chapter 2 of my dissertation examines the effects of peace, the effects of the end of a man-made disaster, using the sudden and unexpected end of the Aceh Insurgency as a natural experiment. I use a population-representative longitudinal survey with during- and post-conflict data, the Study of the Tsunami Aftermath and Recovery. I find that the end of the Aceh Insurgency reallocated female to male labor market activity in 2-year short run. The increase in male labor market activity was driven by the decrease in violence after the end of the insurgency. The increase in male labor market activity and the decrease in economic hardship explained the negative effects of peace on female labor market activity. The negative effects of peace on female labor market activity were stronger for young females and the females in households with a farm, which would be because it may be easier for them to find work with their brawn and farm. The 2-year short-run effects were not significantly different from the 5-year and 10-year effects of peace. The effects were robust to the 2004 Indian Ocean tsunami and earthquake effects, spillover effects, endogenous migration, and endogenous household formation.

Chapter 3 of my dissertation investigates the intergenerational effects of early life

exposure to the Korean War on risk aversion. We use the 7th wave of the Korean Labor & Income Panel Study in a difference-in-differences-type model with both structural and reduced-form estimation methods. Replicating Kim and Lee [2014] by gender, we find new evidence that the first-generation effects of Korean War exposure made only mothers more risk-averse with null effects on fathers. The sons of the affected mothers show the most significant negative intergenerational effects, suggesting parent-child attachment as the key mechanism, in line with the psychology literature on trauma victims. Disassortative mating and differential fertility are ruled out for potential mechanisms as the treatment group does not display disassortative mating and has a similar number of siblings. Negative effects of early-life Korean War exposure on health capital may explain the poor parent-child attachment.

Chapter 4 of my dissertation takes the 2014 *Sewol* ferry disaster as a natural experiment to examine the causal effects of an exogenous psychological shock on time use. The disaster unexpectedly occurred in the middle of the 17th wave of the Korean Labor and Income Panel Study with a spatial concentration of victims in *Ansan* city. Estimates using before-after and difference-in-differences methods indicate that the disaster made males substitute market work for leisure, and females substitute housework for market work and leisure without a TV. The comparison of kernel density distributions before and after the disaster shows that the effects on market work had bidirectional shifts. The evolutions of the effects suggest that most of the effects were persistent until the end of the sample period, 65 days after the disaster. The evidence suggests that disaster-related policies should be not only focused on the direct victims but also extended to a more general population around the affected areas.

Chapter 2

Gendered Local Labor Market Effects of Peace: Evidence from the End of the Aceh Insurgency

The frequency and severity of armed conflicts has been increasing around the world. Not only has the number of conflicts grown by 105% since 2010, but their associated fatalities have risen by 286% (Pettersson et al. 2021). Estimating the effects of the end of conflicts on labor market outcomes is important to understand individual welfare after the end of conflicts. Conflict can affect local labor markets in profound ways, not only during the conflict, but also after it ends. Whether and how the local labor market changes after the end of conflicts is fundamental in optimizing conflict-related policies and understanding the long-term effects of conflict on individual welfare.

Whether peace after a conflict ends would have positive or negative impacts on labor market outcomes is a priori ambiguous. On the one hand, the end of a conflict eliminates violence and uncertainty. Peace may thus lead to a decrease in labor market activity if economic hardship during the conflict had caused individuals to work more (Menon and Van der Meulen Rodgers 2015; Shemyakina 2011). The opposite is also possible if the conflict discouraged individuals from working given the heightened violence and uncertainty (Velásquez 2020). Spillover effects or migration during the conflict may affect local labor demand or supply and introduce another channel. There are only a handful of papers on the effects of peace while the effects of conflicts have gotten relatively more attention in the literature. This paper fills the gap in the literature by examining the effects of peace on labor market outcomes.

The thirty-year-long Aceh Insurgency in Indonesia ended suddenly and unexpect-

edly after the 2004 Indian Ocean tsunami and earthquake to minimize the suffering of the Acehnese people. I examine the effects of peace on individual labor market outcomes and their evolution with a population-representative longitudinal survey, the Study of the Tsunami Aftermath and Recovery, with both during- and post-conflict observations. The effects of peace are identified in a difference-in-differences framework with individual fixed effects using temporal and spatial variation from the end of the Aceh Insurgency. The individuals in rural areas are taken as the treatment group since the insurgency was most aggressive in rural areas. The rest of the individuals in Aceh are used as a control group. Lastly, I document the evolution of the effects of peace over 2-year, 5-year, and 10-year periods.

The Study of the Tsunami Aftermath and Recovery (STAR) provides a unique opportunity to examine the effects of peace. STAR is a population-representative longitudinal survey of Aceh and North Sumatra, Indonesia. The data was based on the 2004 National Socioeconomic Household Survey (SUSENAS) and was collected annually for the following five years and once again in 2015, covering periods both during and after the conflict. It contains rich data on labor market outcomes along with individual, household, and community-level socioeconomic variables. It is worth noting that the STAR follows migrants, which enables this paper to take into account endogenous migration with the end of the Aceh Insurgency.

I find that the end of the Aceh Insurgency significantly reallocated female labor market activity to male labor market activity in the 2-year short run. The increase in male labor market activity was driven by the decrease in violence after the end of the insurgency. The increase in male labor market activity and the decrease in economic hardship explained the negative effects of peace on female labor market activity. The negative effects of peace on female labor market activity were stronger for young females and the females in households with a farm, which would be because

it may be easier for them to find work with their brawn and farm. The short-run effects of peace in 2 years were not significantly different from the 5-year and 10-year effects of peace.

There were spillover effects on male labor market activity in the same direction as the negative effects of peace. The significant spillover effects suggest that the economy of the communities adjacent to the treatment group may have been more active during the insurgency with fewer concerns about the insurgency. Both effects of peace and spillover effects did not lead to significant changes in wages and household welfare. The evidence suggests that the changes in supply and demand had similar orders of magnitude after the end of the insurgency. I show the robustness of the effects of peace by considering the 2004 Indian Ocean tsunami and earthquake, endogenous migration, and endogenous household formation.

This paper makes three contributions to the literature on the causal effects of peace. First, I provide the first evidence on the effects of peace on labor market outcomes. There has been no paper on the causal effects of peace on labor market outcomes, to the best of my knowledge. While Colino [2012] documents the positive effects of temporary truces on labor demand in the Basque conflict, temporary truces are fundamentally different from the permanent end of conflicts. Most of the literature are centered around the ceasefire by the Revolutionary Armed Forces of Colombia (FARC in the Spanish acronym) in Colombia (Bernal et al. 2022; Guerra-Cújar et al. 2020; Prem et al. 2021b; Prem et al. 2020; Prem et al. 2021a). However, the ceasefire brought *partial* peace since FARC and the Colombian government were not the only actors in the conflict. The end of the Aceh Insurgency as *complete* peace not only provides both cleaner identification and interpretation, but also speaks to what we hope to achieve eventually.

Second, this paper contributes to the literature on the effects of peace by ex-

amining the mechanisms underlying the effects and linking the mechanisms to the conflict literature through a model. Due to the lack of evidence in the literature, it is not clear if the elimination of violence and uncertainty with peace is the opposite of the introduction of violence and uncertainty with conflicts. For example, a damaged economy and infrastructure during the conflict period may introduce migration or negative spillover effects (Besley and Mueller 2012; Guidolin and La Ferrara 2007). I find that the substitution of male and female labor market activity within households with violence and economic hardship is the primary mechanism, similar to the conflict literature (Galdo 2013; Kondylis 2010; Shemyakina 2011).

Third, I contribute to the literature by examining the evolution of the effects of peace. While the evolution of the effects of peace on deforestation, education, violence, and entrepreneurship were examined in Colombian conflict (Bernal et al. 2022; Prem et al. 2020; Prem et al. 2021a; Prem et al. 2021b), there has been no study on the evolution of the effects of peace on labor market outcomes. Documenting the effects of peace on labor market outcomes and their evolution is essential in optimizing policy interventions as individuals make their living in the labor market. A few papers argue that the empirical pattern of international aid is not healthy for post-conflict recovery (Collier et al. 2003, Suhrke and Buckmaster 2005). I help inform the understanding of the timing and size of policy interventions by examining the effects of peace on labor market outcomes and their evolution.

Section I describes the context and data. Section II lays out a theoretical motivation to clarify the effects of the end of the Aceh Insurgency. The identification strategy and results are presented in section III. Section IV examines the mechanisms, and section V tests the robustness of the results. Section VI investigates the heterogeneous effects of peace by individual characteristics. Section VII covers the evolution of the effects, and finally, section VIII concludes. Supplemental materials

are available in the Appendix.

2.1 Context and Data

The sudden and unexpected end of the thirty-year-long Aceh[1] Insurgency in Indonesia was catalyzed by the 2004 Indian Ocean tsunami and earthquake (Barron 2008; Monecke et al. 2008). A unilateral ceasefire by the insurgents, the Free Aceh Movement (GAM in Indonesian acronym), was declared after the tsunami to minimize the sufferings of the Acehnese people. The subsequent international involvement, reconstructions, and business opportunities with peace dividends to the Free Aceh Movement elites contributed to the success of the peace agreement of August 15, 2005 (Aditjondro 2007; Waizenegger 2007). The peace has lasted since the peace agreement.

The third and last phase of the Aceh Insurgency started with the fall of President Suharto and lasted from 1999 to 2005 after the end of the second phase around 1992. The Free Aceh Movement promoted the independence of Aceh contending that Javanese are exploiting Acehnese. The feeling of exploitation has been lingering from the economic grievances since when huge oil and natural gas deposits were found in Aceh in the 1970s and the locals were kept out of prosperity. The first and second phases of the insurgency were overwhelmed by the Indonesian security forces. However, the fall of Suharto, suppression by the government security forces after the second phase of the insurgency, and the success of the independence referendum of East Timor all contributed to the third phase of the Aceh insurgency through the increase in hatred and nationalism against Javanese and the Indonesian government (Aspinall 2009).

[1]Aceh is a province of Indonesia, located on the northern tip of Sumatra island.

Aceh was under martial law and was highly restricted by the government before the 2004 Indian Ocean tsunami and earthquake, especially since the failure of the previous peace talk in 2003. The Free Aceh Movement employed a guerrilla strategy in rural areas (Aspinall 2009). Economic activities were restricted by fear and uncertainty, especially at certain times of the day (Tajima 2010), although only 1% of males joined any of the fighting groups according to the Aceh Reintegration and Livelihood Survey. As a consequence, female household members often helped earn extra income during the insurgency (Amnesty International 2004).

The Study of the Tsunami Aftermath and Recovery (STAR) provides a unique opportunity to examine the causal effects of peace on labor market outcomes. It is a population-representative longitudinal survey of Aceh and North Sumatra. Each household member of age 15 and older is individually surveyed in each wave of STAR. Its baseline sample is taken from the 2004 National Socioeconomic Household Survey (SUSENAS), a nationally representative household survey conducted by Statistics Indonesia in February/March 2004, 10 months before the 2004 Indian Ocean tsunami and earthquake and the Free Aceh Movement's unilateral ceasefire. Every household member in the 2004 SUSENAS was eligible for follow-up survey and 95% of the tsunami survivors were interviewed during the one-year follow-up wave. Four more annual and 10-year follow-up surveys were conducted (Frankenberg et al. 2011; Frankenberg and Thomas 2017; Ho et al. 2017).

Figure 2.1 shows the timeline of the Aceh insurgency with the STAR data collection. The baseline during-conflict wave and the post-conflict 2-year follow-up wave are employed to examine the short-run effects of the end of the Aceh Insurgency. The medium- and long-run effects are explored using the baseline wave with the post-conflict 5-year and 10-year follow-up waves. The 1-year follow-up wave was conducted between May 2005 and June 2006, which covers the period after the Free Aceh

Movement's unilateral ceasefire but overlaps with the peace agreement of August 15, 2005. Thus, the 1-year follow-up wave is not used in the analysis as it is difficult to assign the wave neither as during-conflict nor post-conflict period.

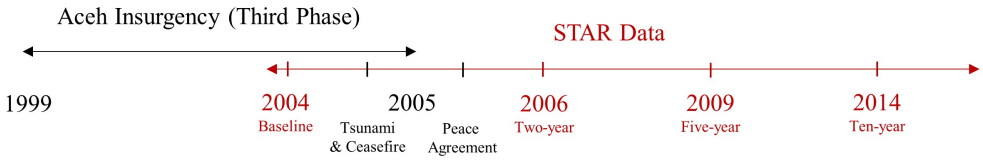

Figure 2.1: Timeline

Note: This figure shows the timeline of the third phase of the Aceh Insurgency along with the 2004 Indian Ocean tsunami and the ceasefire in December 2004, the Peace Agreement in 2005, and the Study of the Tsunami Aftermath and Recovery data collection from 2004 to 2014. This paper uses the 2004 during-conflict and the 2006 2-year follow-up waves for the main analyses. Labor market dynamics are further explored using the 5-year and the 10-year follow-up waves.

Figure 2.2 shows the spatial distributions of the insurgency-related homicide rates (per 100,000) in Aceh over time. The darker color implies higher homicide rates, and the red buffers outline the tsunami-damaged areas suggested by the USAID (Gray et al. 2014). Panel A shows the distribution right before the ceasefire, the year of the during-conflict baseline wave. We can see a substantial variation in the homicide rates across Aceh while the tsunami damages are concentrated on the coastlines. The insurgency was most active in rural areas. The influence of the tsunami is discussed further in the robustness checks section. Panel B plots the distribution for the year of the peace process, and we can see that the insurgency-related homicide rates had not yet converged to zero. The ongoing insurgency-related homicides in 2005 make it difficult to assign the 2005 wave neither as during-conflict nor peace periods. Panel C shows that insurgency-related homicide rates converged to zero by 2006, and the peace continued since then. Therefore, the 2004 during-conflict baseline wave can be compared to the 2006 2-year follow-up wave to estimate the short-run effects of peace.

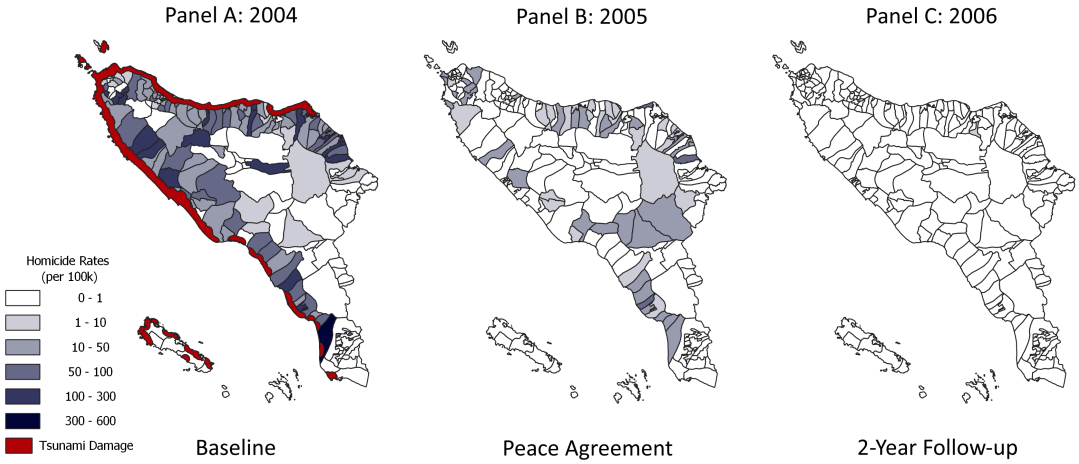

Figure 2.2: Insurgency-related homicide rates (per 100,000) 2004-2006

Note: This figure displays the temporal and spatial distributions of the insurgency-related homicide rates (per 100,000) in the last 12 months from 2004 to 2006. Panel A shows the variation for the year of the during-conflict baseline wave. Panels B and C show the distributions for the year of the Peace Agreement and the year after the end of the Aceh Insurgency. The National Violence Monitoring System (NVMS), the 2003 Village Potential Statistics (PODES), and the 2005 Indonesian Census are used to calculate the community-level insurgency-related homicide rates (per 100,000) in the last 12 months.

The individuals of age 25-59, as of the 2004 during-conflict baseline wave, are considered to rule out potential confounding effects from schooling and retirement. The baseline sample consists of 7,760 individuals interviewed both in during-conflict baseline and 2-year follow-up waves. The attrition rate is 5.2% for the 2-year follow-up wave[2]. Table 2.1 shows the descriptive statistics of the during-conflict baseline wave sample. Columns (1) and (2) summarize the mean and standard deviations of the entire baseline wave sample, and the sample is stratified in columns (3) and (4) by gender. Panel A shows the outcome variables. While 91% of the males worked as their primary activity in the past week, only 25% of females did. Given employed,

[2]The individuals in rural areas are significantly less likely to be attrited, and younger and more educated individuals are more likely to be attrited. The individuals in rural areas are less mobile with their lands, so relatively low attrition in the rural area is not surprising. While there may be seasonal migrations, the STAR proxy-interviews another household member. Given that younger and more educated individuals are more likely to work, the selective attrition may introduce positive bias to the effects of peace.

males and females had 42 and 32 working hours, respectively. In contrast, only 1% of males did housework as their primary activity in the past week while 71% of females did. The stark gender differences suggest that male and female samples should be considered separately. Indeed, the Indonesian labor market is male-dominant, and the conflict literature reports distinct effects by gender (Galdo 2013; Shemyakina 2011; Kondylis 2010).

Panel B shows that 74% of the sample is in the treatment group. Individuals in rural communities are assigned as the treatment group. The average insurgency-related homicide rates (per 100,000) were 36.16 and 12.98 for rural and urban areas, respectively, for the year before the end of the insurgency. The tension between the government security forces and the Free Aceh Movement was highest in the rural areas as the Free Aceh Movement was most active in the rural areas (Tajima 2010). I use the rural indicator to approximate the ideal treatment group, the individuals affected by the violence and uncertainty of the insurgency. I do not use insurgency-related homicides in the main analysis for the pre-trend and media bias issues, which I discuss further below along with the identification strategy. Panel C reports the individual characteristics of the sample. The average male and female sample individuals are married rural residents in their late 30's with a primary school degree.

2.2 Theoretical Motivation

A utility maximization problem for a unitary household model, adapted from Becker and Rubinstein [2011], can help clarify the effects of peace on labor market outcomes and its potential mechanisms. I consider a two-person unitary household model for parsimony[3]. During a conflict, a two-person household of a male and a female maxi-

[3]The core message does not change with a collective household model or a household with more than two members.

Table 2.1: During-Conflict Descriptive Statistics

	(1) Mean	(2) Std. Dev.	(3) Male	(4) Female
Panel A. Outcomes				
Work	0.57	0.49	0.91	0.25
Working hours	39.43	13.99	42.23	32.33
Housework	0.37	0.48	0.01	0.71
Panel B. Treatment group				
Rural	0.74	0.44	0.74	0.74
Panel C. Covariates				
Age	38.15	9.14	38.50	37.81
Years of education	7.14	4.76	7.58	6.73
Married	0.80	0.40	0.82	0.79
Log per capita real expenditure	12.03	0.54	12.04	12.02
Household size	4.85	1.93	4.87	4.84
Number of male household members age 20-64	1.34	0.82	1.46	1.24
Sample Size		7,760	3,753	4,007

Note: This table reports the during-conflict wave (2004) mean and standard deviation in columns (1) and (2). Columns (3) and (4) report the male and female averages. The individuals in the rural communities are taken as a treatment group as the insurgency was most aggressive in rural areas. The rest of the individuals in Aceh are taken as a control group.

mizes the expected utility:

$$\max_{l_g,h_g,c_g} U = \sum_{g=m,f} s_g(l_g,\tau)u_g(c_g,x_g,1-l_g-h_g) \qquad [1]$$

where subscript g denotes the gender. $s(\cdot)$ is the probability of surviving, l indicates the time spent on work, τ represents the local Aceh Insurgency activity perceived by the individual. $u(\cdot)$ is the individual utility from consuming market goods c and home goods x. h is housework time spent in producing home goods x, and leisure is $1-l-h$. The utility maximization is subject to the following budget constraint: $\sum_{g=m,f} s_g(l_g,\tau)\{p_g^c c_g - p_g^x x_g - w_g l_g\} = I$ [2] where w is wage, and I indicates nonlabor income with gender-specific prices for market and home goods p^c and p^x.

The economic agent decides the optimal level of labor market activity by balancing the marginal utility of increasing a unit in work, housework, and leisure. Balancing the marginal utilities operates both at the individual and household levels as home

goods x is shared by household members. Work becomes a function of surviving probabilities, wages, prices, and nonlabor income: $l = l(\mathbf{s}, \mathbf{w}, \mathbf{p}, I)$. The effects of local Aceh Insurgency activity on labor market activity are the following:

$$\frac{\Delta l_g}{\Delta \tau} = \underbrace{\overbrace{\frac{\Delta l_g}{\Delta s_g}}^{\geqslant 0} \times \overbrace{\frac{\Delta s_g}{\Delta \tau}}^{\leqslant 0}}_{\substack{\text{Discouraged-Worker} \\ \text{Effects} \\ \text{(Substitution)}}} + \underbrace{\overbrace{\frac{\Delta l_g}{\Delta s_{-g}}}^{\leqslant 0} \times \overbrace{\frac{\Delta s_{-g}}{\Delta \tau}}^{\leqslant 0}}_{\substack{\text{Added-Worker} \\ \text{Effects} \\ \text{(Income)}}} + \cdots \qquad [3]$$

where subscript $-g$ denotes the other household member.

The model highlights two major effects of the local Aceh Insurgency activity during the insurgency. First, the local Aceh Insurgency activity would decrease surviving probability and discourage working, which is referred to as the Discouraged Worker Effects (Lundberg 1985). The agent would decrease labor market activity to increase the surviving probability, i.e., there is a substitution between labor market activity and surviving probability. Second, the decrease in the other household member's labor market activity would decrease household income, which motivates the agent's labor market activity. The income effect is called the Added Worker Effects (Lundberg 1985).

The Discouraged Worker Effects and the Added Worker Effects disappear after the sudden and unexpected end of the Aceh Insurgency, and the effects of peace would be the opposite of the during-conflict effects. That is, the effects of peace would be positive if the Discouraged Worker Effects were dominant during the insurgency and negative if the Added Worker Effects were dominant. The fact that males were the primary breadwinners and worked longer hours suggests that the Discouraged Worker Effects would be stronger for males (Tajima 2010).

Hypothesis 1: *The effects of peace would be positive on males as the Discouraged Worker Effects are greater than the Added Worker Effects.*

Females often worked for extra income due to economic hardship during the insurgency (Amnesty International 2004). Thus, females would be more keen on decreasing their labor market activity as the increase in male labor market activity resolves economic hardship after the end of the insurgency.

Hypothesis 1: *The effects of peace would be negative on females as the Added Worker Effects are greater than the Discouraged Worker Effects.*

One caveat is that there may be some inertia in labor market activity even after the end of the conflict (Acemoglu et al. 2004), which would bias the estimates towards zero.

2.3 Short-Run Effects of Peace

2.3.1 Individual-level Results

The net effects of the end of the Aceh Insurgency could be identified in a difference-in-differences framework exploiting the temporal and geographic variation of the Aceh Insurgency:

$$Y_{it} = \alpha_0 Peace_t + \alpha_1 Peace_t \times Rural_i + X_{it}\Gamma_I + \delta_i + \epsilon_{it} \qquad [4]$$

where the subscript i indicates individual, k represents the community of the during-conflict baseline wave, and t is the survey wave. *Peace* is the peace period indicator,

and *Rural* is the indicator for rural area residents. The outcome variable Y includes indicators for working as the primary activity in the past week, doing housework as the primary activity in the past week, and working hours if employed. Individual fixed effects δ_i absorbs time-invariant covariates. Individual covariates X include age and year-by-month fixed effects. Standard errors are clustered on the community of the during-conflict baseline wave throughout the paper.

The treatment group is defined as individuals in rural areas. The Free Aceh Movement was most active in the rural areas, so the tension between the government security forces and the Free Aceh Movement was highest in the rural areas (Tajima 2010). The ideal treatment group would be the individuals affected by the violence and uncertainty of the insurgency. While I could have specified the treatment group with the insurgency-related homicide as a measure of the violence and uncertainty, it was not feasible to obtain pre-trends with the homicide[4], not to mention the media bias. As I proxy the treatment group with the rural indicator, the estimates should be considered as an Intent-to-Treat. The treatment group is assigned as of the during-conflict baseline wave community instead of the current survey wave community to exclude endogenous migration concerns.

Table 2.2 reports the α_1 estimates of the equation [4], the estimated effects of peace. In line with the hypotheses, the effects of peace were positive on male labor market activity and negative on female labor market activity. We can see a positive but insignificant effect of peace on male working hours, which explains 6% of the baseline average. The effects of peace were significantly negative for female work, and we can find the corresponding positive effects on female housework. The effects of peace on female work and housework account for 60% and 18% of the baseline mean,

[4]I take pre-trends from the National Labour Force Survey (SAKERNAS), which does not provide geocode to match the insurgency-related homicide in figure 2.2. Fortunately, the SAKERNAS provides rural and urban information, from which I trace out pre-trends.

respectively. Interestingly, we can see a marginally significant increase in female working hours. The increase in female working hours would be due to the selection and the inertia in labor market activity (Acemoglu et al. 2004). Note that the estimated effects of peace are not significantly different even when the treatment group is defined as the communities with any insurgency-related homicide in 12 months (see table A1).

Table 2.2: Short-Run Individual-level Results

	Male	Female
	(1)	(2)
Panel A: Work (Extensive)		
Peace × Rural	-0.03	-0.15***
	(0.02)	(0.03)
Baseline mean	0.91	0.25
Observations	3,753	4,007
Panel B: Working Hours (Intensive)		
Peace × Rural	2.45	3.58*
	(1.56)	(1.83)
Baseline mean	42.23	32.33
Observations	3,246	816
Panel C: Housework		
Peace × Rural	-0.00	0.13***
	(0.01)	(0.03)
Baseline mean	0.01	0.71
Observations	3,753	4,007

Note: This table reports the coefficient estimates of equation [4], regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Identification of the difference-in-differences method critically depends on the parallel trends between the treatment and control groups. While figures A1 and A2 show the non-parallel pre-trends of both extensive and intensive margins of labor market activity, the difference-in-differences method could be validated as far as the trends are taken into account (Rambachan and Roth 2022; Bilinski and Hatfield 2018). I took the difference of the maximum and minimum difference in the pre-trends be-

tween the treatment and control groups as the possible violation of parallel trends Δ. That is, I added and subtracted the absolute value of the possible violation of parallel trends from the original estimate to set-identify the effects of peace. The negative effects of peace on female work still persist even after the adjustments (see table A2).

The pre-trends adjustment should be taken with a caveat that there was a significant spatial and temporal variation in the Aceh Insurgency activity. The correlation in insurgency-related homicide rates between the baseline year 2004 and any earlier year of the third phase of the Aceh Insurgency ranges from 0.07 to 0.39. The significant temporal variation in the insurgency intensity from the failure of peace talks in 2003 and the subsequent announcements of military and civil emergencies indicates the instability of the insurgency and the limitations of the pre-trends (see figure A3).

The other core assumption is that the effects of peace on the control group should be in the same direction as the treatment group, if any. The state of living in the control community during the conflict period would not be the same as living in the peace period, leading to a concern about a contaminated control group. The estimated effects of peace would be an underestimate if the effects of peace on the treatment and control groups are in the same direction, which depends on the spillover effects of peace. I test whether the introduction of spillover effects changes the original effects of peace estimates in the robustness section.

2.3.2 Household-level Results

As the model suggests balancing marginal utilities within the household, the following household-level difference-in-differences model could be used to examine how

household-level labor market activity changed after the end of the Aceh Insurgency:

$$Y_{ht} = \beta_0 Peace_t + \beta_1 Peace_t \times Rural_h + X_{ht}\Gamma_H + \delta_h + \epsilon_{ht} \qquad [5]$$

where subscript h indicates household as of the during-conflict baseline wave. To parsimoniously estimate the household-level response to peace, I restrict the sample to the households of a husband and a wife with any number of non-adult children. The outcome variable Y includes indicators for both husband and wife work/housework, only husband work/housework, only wife work/housework, and their total and individual working hours. Standard errors are clustered on the community of the during-conflict baseline wave.

Table 2.3 reports the estimates of the equations [5]. Panel A suggests that the effects of peace were negative on the wife's work, in line with the individual-level results in table 2.2. In panel B, both male and female working hours increased. The total working hours in panel B are considered when both husband and wife worked in both waves. The total working hours significantly increased by 13%, possibly due to the inertia in labor market activity even after the end of the conflict (Acemoglu et al. 2004). Panel C considers the unconditional working hours including no work as zero value. We can find a significant increase in the husband's unconditional working hours and a marginally significant decrease in the wife's unconditional working hours. It is surprising that the magnitudes of the changes in unconditional working hours are almost identical. The effects are economically meaningful. The increase and decrease in male and female unconditional working hours account for 9% and 47% of the baseline average. The household-level results corroborate the reallocation of female to male labor activity after the end of the insurgency.

Table 2.3: Short-Run Household-level Results

	Both	Husband	Wife
	(1)	(2)	(3)
Panel A: Work (Extensive)			
Peace × Rural	-0.08**	0.01	-0.10***
	(0.04)	(0.02)	(0.04)
Baseline mean	0.14	0.98	0.15
Observations	1,336	1,336	1,336
Panel B: Working Hours (Intensive)			
Peace × Rural	9.62*	2.27*	3.32
	4.82	(1.29)	(3.27)
Baseline mean	74.38	42.29	33.68
Observations	169	1,313	186
Panel C: Working Hours (Including Zero)			
Peace × Rural	0.02	3.64**	-3.63*
	(2.73)	(1.45)	(1.92)
Baseline mean	49.80	42.01	7.79
Observations	1,336	1,336	1,336
Panel D: Housework			
Peace × Rural	-0.00	-0.00	0.09***
	(0.01)	(0.01)	(0.03)
Baseline mean	0.00	0.00	0.84
Observations	1,336	1,336	1,336

Note: This table reports the coefficient estimates of equation [5], regressing the household-level labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with household fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.4 Mechanisms

2.4.1 Violence

The Aceh Insurgency was violent and fearful. Anonymous homicides were common and the bodies were often found by roadsides or in fields. The insurgency took almost four civilian lives for every fatality in government security forces or the Free Aceh Movement. The civilian casualties resulted in the process of extortion or decreasing the support for the enemy. The locals were afraid of going to work to remote areas, where the Free Aceh Movement was active (International Crisis Group 2002; Tajima 2010).

The role of violence could be investigated using the insurgency-related homicide during the insurgency with the following model:

$$Y_{it} = \gamma_0 Peace_t + \gamma_1 Peace_t \times Rural_i + \gamma_2 Peace_t \times Homicide_k + \gamma_3 Peace_t \times Rural_i \times Homicide_k + X_{it}\Gamma + \delta_i + \nu_{it} \quad [6]$$

where $Homicide$ is defined as the individuals in the communities with the top 10% recent[5] insurgency-related homicide rates. The rest of the specification is the same as equation [4] except for the inclusion of $Peace \times Homicide$ and $Peace \times Rural \times Homicide$. The coefficient of interest γ_3 from the triple interaction with $Homicide$ summarizes the effects of peace from the elimination of violence[6]. Standard errors

[5]Recent homicide is defined as homicide within 12 months from the during-conflict interview date. Individual perceptions of the insurgency would be a weighted average of the history of past insurgency activities and future expectations, which may not be best represented by an arbitrary 12-month window. The 12-month window is used as a baseline to make the results comparable to other estimates in the literature (e.g. Velásquez 2020). The top 10% insurgency-related homicide rate threshold is about 5 per 100,000.

[6]The beliefs about the stability of peace may be an issue. According to the Aceh Reintegration and Livelihood Survey in 2008, only 70% of the sample was positive about the stability of peace for

are clustered on the during-conflict baseline wave community.

The National Violence Monitoring System (SNPK) is used to obtain monthly community-level violence data. SNPK covers Aceh and eight other provinces with a higher level of violence since 1998 and further extends its coverage to sixteen provinces after 2005. The main source of the data is local newspapers, which provide the best available measure of local perception of the insurgency. The SNPK considered coverage, accuracy, censorship, and archive completion of newspapers to check the validity of the reports. For example, the newspapers with the best geographic coverage were selected by considering the number of offices and reporting staff. The accuracy of the reports was assessed with the fact-checking policy and sources of the newspaper. Censorship and reporting were checked by interviewing newspaper staff, and the completeness of the archive was maintained in the field (Barron et al. 2009). STAR and SNPK are merged with the individual's interview date and community of the during-conflict baseline wave in 2004.

Table 2.4 reports the estimates of the equation [6]. We can see that the effects of peace in the communities with the top 10% insurgency-related homicide rates are very significant for males in panel B. The sizable increase explains 16% of the baseline mean and suggests that violence was a significant factor in decreasing working hours during the insurgency. In column (2), we can find the negative effects of peace on female work concentrated in the communities with any insurgency-related homicide, although it is not significant. The evidence suggests that violence during the insurgency was a significant factor in the labor market response after the end of the insurgency.

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the next two years. While 27% either refused to answer or chose "don't know", 3% of the sample was negative about peace in the next two years. The results would be biased toward zero as the disbelief about peace was more prevalent.

Table 2.4: Heterogeneity of Peace by High Insurgency Homicide

	Male	Female
	(1)	(2)
Panel A: Work (Extensive)		
Peace × Rural	-0.04*	-0.14***
	(0.02)	(0.03)
Peace × Homicide	0.03	0.20
	(0.04)	(0.13)
Peace × Rural × Homicide	0.04	-0.09
	(0.04)	(0.12)
Panel B: Working Hours (Intensive)		
Peace × Rural	1.34	3.08
	(1.54)	(2.00)
Peace × Homicide	-0.78	-3.79
	(1.94)	(3.81)
Peace × Rural × Homicide	6.92**	4.28
	(3.13)	(3.72)
Panel C: Housework		
Peace × Rural	0.00	0.13***
	(0.01)	(0.03)
Peace × Homicide	0.01	0.18
	(0.02)	(0.15)
Peace × Rural × Homicide	-0.03	-0.09
	(0.02)	(0.13)

Note: This table reports the coefficient estimates of equation [6], regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, the indicator for the top 10% insurgency-related homicide *Homicide*, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.4.2 Economic Hardship

Economic concerns were most pressing during the Aceh Insurgency. According to a retrospective question in the Aceh Reintegration and Livelihood Survey, over 63 percent of the sample answered that money/food/job were the most pressing concerns during the conflict period (see figure 2.3). In contrast, at most 20 percent of the sample answered security as a primary concern. Economic hardship from conflict and the subsequent increase in female work are well-documented both in articles about the Aceh Insurgency (Amnesty International 2004; International Crisis Group 2002; Tajima 2010) and in the conflict literature (Menon and Van der Meulen Rodgers 2015; Shemyakina 2011).

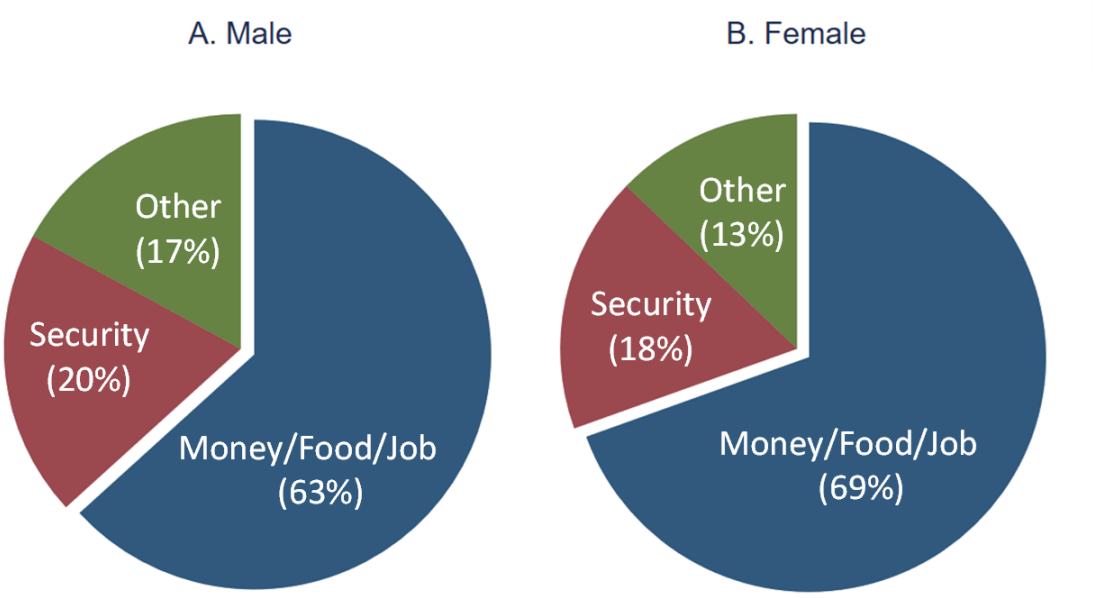

Figure 2.3: Concerns during the Aceh Insurgency (Jan 2001-Aug 2005)

Note: This figure documents the most pressing concerns at the time of the Aceh Insurgency. A retrospective question (Q125) in the Aceh Reintegration and Livelihood Survey (ARLS) is used for the figure. The sample born between 1945 and 1979 is used to cover the same working-age population as the main sample. While the male sample is representative of the population of Aceh as of 2008 by the survey design, the female sample is not.

The transitory nature of female work corroborates that economic hardship increased female work during the insurgency. Agriculture was the largest sector females worked in both before and after the end of the Aceh Insurgency. Unless the community was fully controlled by the government security forces, economic activities were hindered by the tension between the Free Aceh Movement and the government security forces. Plantation works on the hillside were often restricted by the government security forces, and working on the farms in flatland areas became the most accessible (Tajima 2010). It is striking that only 25% of the during-conflict female agricultural workers stayed working in the agricultural sector 2 years after the end of the Aceh Insurgency. On the contrary, 63% of the during-conflict female non-agricultural workers stayed working in the non-agricultural sector, and 73% of during-conflict females doing housework kept doing housework. The 75% attrition rate of the during-conflict female agricultural workers is taken as revealed preferences that they would not have worked as much if there were no insurgency (see figure 2.4).

2.4.3 Wages and Non-Labor Income

The end of the Aceh Insurgency may have affected the demand for male and female labor. If the labor demand drives the positive effects of peace on male working hours and the negative effects of peace on female work, male wages should grow faster than female wages in the treatment group. I estimate the short-run effects of peace on hourly wages with equation [4]. Unfortunately, wage data for self-employed individuals was not collected by Statistics Indonesia in the during-conflict baseline wave. Thus, the estimates with no self-employed individuals should be interpreted with the caveat that the results may not be representative of the sample directly affected by the insurgency.

Figure 2.4: Female Transition Before/After the End of the Insurgency

Note: This figure documents the 2-year post-conflict transition distributions of the female sample. The blue bar is for the during-conflict female workers in the agriculture sector, the red bar is for the ones in the non-agriculture sector, and the green bar is for the ones doing housework. The x-axis indicates the sector of the 2-year post-conflict period while the y-axis represents the proportion of the sample. The Study of the Tsunami Aftermath and Recovery (STAR) is used to calculate the sample average.

Table 2.5 reports the estimates of the effects of peace on male and female hourly wages. We can find overall insignificant and negative effects of peace in panel A. In panel B, the effects are also not particularly stronger in the communities with the top 10% insurgency-related homicide rates, where the increase in male working hours is most significant. The insignificant changes in wages suggest that both supply and demand increased by similar orders of magnitude. The evidence suggests that wages may not be the primary mechanism underlying the effects of peace.

Non-labor income shock could be another possibility. The negative economic shock during the conflict period (Amnesty International 2004; International Crisis

Group 2002; Tajima 2010) and post-conflict adjustments may explain the increase in male working hours. However, it does not explain why the treatment group females did not. Therefore, non-labor income shock would not be driving the effects of peace.

Table 2.5: Short-Run Effects of Peace on Wages

	Male	Female
	(1)	(2)
Panel A: Baseline		
Peace × Rural	-0.17	-0.50
	(0.61)	(0.52)
Panel B: Insurgency Homicide		
Peace ×Rural	-0.15	-0.56
	(0.65)	(0.57)
Peace ×Homicide	-1.08	0.00
	(0.99)	(0.77)
Peace ×Rural ×Homicide	0.28	0.30
	(1.30)	(1.29)
Baseline mean	5.71	6.48
Observations	803	282

Note: This table reports the coefficient estimates of equation [4], regressing the wages on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with age, year-by-month, and individual fixed effects. The extreme 5% of wage data is winsorized on each tail. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.4.4 Prices

The effects of peace may have been driven by price changes. If relative price decreases in rural areas after the end of the insurgency, especially for food items, the effects of peace would be negative for female labor market activity. While price data is not available, per capita expenditure and the proportion of food expenditure can be used to proxy household welfare that the price changes would primarily affect. Table 2.6 reports the estimates with equation [4]. It is reassuring that the effects of peace were insignificant on both expenditure and proportion of food for both male and female sample.

Table 2.6: Short-Run Effects of Peace on Household Welfare

	Male (1)	Female (2)
Panel A: Expenditure		
Peace × Rural	-0.02	-0.01
	(0.08)	(0.08)
Baseline mean	12.04	12.02
Observations	4,006	3,752
Panel B: Proportion of Food		
Peace × Rural	-2.34	-2.22
	(1.87)	(1.74)
Baseline mean	67.25	67.05
Observations	4,003	3,743

Note: This table reports the coefficient estimates of equation [4], regressing the household welfare outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.5 Robustness Checks

2.5.1 The 2004 Indian Ocean Tsunami and Earthquake

The impact of the 2004 Indian Ocean tsunami and earthquake on the validity of the difference-in-differences estimates is a major concern. To test the concern, I additionally include an indicator for the tsunami-damaged villages and its interaction with the peace indicator in equation [4] to control for the effects of the tsunami. If the effects of peace estimates are significantly affected by the inclusion of the tsunami variables, the effects of peace without the tsunami control may be capturing the contemporaneous tsunami effects. Table 2.7 reports the estimates. We can see that the estimated effects of peace are not significantly different from the original estimates in table 2.2, and their magnitudes are very similar. The evidence suggests that the end of the Aceh Insurgency had its own effects on labor market outcomes, apart from the 2004 Indian Ocean tsunami and earthquake.

Table 2.7: Robustness Test with the Tsunami Effects

	Male	Female
	(1)	(2)
Panel A: Work (Extensive)		
Peace × Rural	-0.03	-0.15***
	(0.02)	(0.03)
Observations	3,753	4,007
Panel B: Working Hours (Intensive)		
Peace × Rural	2.42	3.50*
	(1.50)	(1.83)
Observations	3,246	816
Panel C: Housework		
Peace × Rural	-0.00	0.13***
	(0.01)	(0.03)
Observations	3,753	4,007

Note: This table reports the coefficient estimates of equation [4] with the tsunami effects, regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, the interaction term between *Peace* and *Rural*, the indicator for any tsunami damage *Any*, and the interaction term between *Peace* and *Any* along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.5.2 Spillover Effects

The end of the Aceh Insurgency may have spatial spillover effects on labor market outcomes. For example, the economy of the communities adjacent to the treatment group could have been more active during the insurgency with fewer concerns about the insurgency. It could be the opposite if there were spatial spillovers of violence and uncertainty. I examine the spillover effects by introducing an indicator for the adjacent communities *Spillover* and its interaction with *Peace* with equation [4]. If there are significant spillover effects, we would find either a significant change in the coefficient estimates of $Peace \times Rural$ or a significant coefficient estimate of $Peace \times Spillover$.

Table 2.8 reports the estimated effects of peace as well as the spillover effects. We can find that the effects of peace got significant for male work, although it is not

significantly different from the original estimate without the spillover terms in table 2.2. It is intriguing that we can find significant spillover effects for male work and housework. The negative spillover effects for male work imply that males worked more in the communities adjacent to the treatment group during the insurgency, possibly with a more vibrant economy. The males reduced work and increased housework after the end of the insurgency. For females, the estimated effects of peace are not significantly different from the original estimates in table 2.2, and the spillover effects are both statistically and economically insignificant. Interestingly, the spillover effects on wages and household welfare are not significant, which suggests that there were similar increases in both supply and demand (see table A3).

Table 2.8: Short-Run Spillover Effects

	Male	Female
	(1)	(2)
Panel A: Work (Extensive)		
Peace × Rural	-0.04*	-0.15***
	(0.02)	(0.03)
Peace × Spillover	-0.08**	-0.01
	(0.03)	(0.05)
Observations	3,753	4,007
Panel B: Working Hours (Intensive)		
Peace × Rural	2.39	3.49*
	(1.62)	(1.90)
Peace × Spillover	-0.41	-0.62
	(3.22)	(4.08)
Observations	3,256	816
Panel C: Housework		
Peace × Rural	0.00	0.14***
	(0.00)	(0.03)
Peace × Spillover	0.03**	0.04
	(0.01)	(0.05)
Observations	3,753	4,007

Note: This table reports the coefficient estimates of equation [4] with spillover effects, regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, the interaction term between *Peace* and *Rural*, the indicator *Spillover* for the communities adjacent to the treatment group, and the interaction term between *Peace* and *Spillover* along with age and year-by-month fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.5.3 Endogenous Migration

Individuals may move for economic opportunities after the end of the insurgency. While individual fixed effects partially alleviate the potential selection by taking care of the time-invariant factors, the endogenous migration with peace remains as a concern for the validity of the estimates. It is reassuring that STAR follows migrants from the baseline during-conflict wave. So far, the treatment group is defined as the during-conflict baseline wave community to resolve the endogenous migration issue. While over 87% of the sample still reside in the during-conflict baseline wave community as of the 1-year follow-up wave, measurement errors from migration could decrease the precision of the estimates.

The significance of migration can be tested by using an alternative treatment defined as of the 2-year follow-up community, instead of the during-conflict baseline community. Table 2.9 shows the estimates of equation [4] with the rural area defined at the 2-year follow-up community. The estimates are not significantly different from the estimates in table 2.2. Indeed, individual migration responses to peace were not systematically different between the treatment and control groups. Both migrations from the birth community and from the baseline during-conflict community were not significantly differently affected by the end of the Aceh Insurgency between the treatment and control groups, when they were used as the outcome variables with equation [4] (see table A4).

2.5.4 Endogenous Household Formation

Endogenous household formation is another concern. The end of the insurgency may have affected the household structure, which could influence labor market activities (Hamoudi and Thomas 2014). If working-age males joined the household after the end

Table 2.9: Robustness Test with Migration

	Male (1)	Female (2)
Panel A: Work (Extensive)		
Peace × Rural	-0.03	-0.12***
	(0.02)	(0.03)
Observations	3,751	4,006
Panel B: Working Hours (Intensive)		
Peace × Rural	1.57	3.86**
	(1.65)	(1.84)
Observations	3,235	816
Panel C: Housework		
Peace × Rural	0.00	0.11***
	(0.01)	(0.03)
Observations	3,751	4,006

Note: This table reports the coefficient estimates of equation [4] with an alternative definition of the treatment group, regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural* defined as of the 2-year follow-up wave, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

of the insurgency, females may decrease their labor market activity. To investigate the effects of peace on endogenous household formation, household size, number of working-age male household members, number of under-five household members, and average adult height are used as outcome variables with equation [4] to approximate the household structure and human capital of household members.

Table 2.10 shows the estimated effects of peace on the household structure and human capital of household members. In columns (1)-(3), we can see that the household size, number of working-age male household members, and number of under-five household members significantly increased in rural areas after the end of the insurgency with null effects on average household adult height. The evidence suggests that endogenous household formation may help explain the effects of peace. To test whether household formation is the dominant channel for the effects of peace, I repli-

cate the analysis with the couples subsample as the negative effects of peace were also strong for the females in couples. There is no significant increase in working-age males for couples (see table A5). While there is a significant increase in the number of under five children, the insignificant evolution of the effects of peace over until 10 years after peace suggests that household formation is not the primary mechanism (see figure 2.5). Therefore, endogenous household formation would not be the primary mechanism underlying the effects of peace.

Table 2.10: Short-Run Effects of Peace on Household Composition

	Household Size	Number of HH Males 20-64	Number of HH Members 0-4	Mean HH Adult Height
	(1)	(2)	(3)	(4)
Panel A: Male				
Peace × Rural	0.50***	0.15***	0.07**	-0.07
	(0.10)	(0.04)	(0.03)	(0.13)
Baseline mean	4.87	1.46	0.51	157.5
Sample size	3,753	3,753	3,753	3,748
Panel B: Female				
Peace × Rural	0.42***	0.12***	0.07**	0.15
	(0.09)	(0.04)	(0.03)	(0.09)
Baseline mean	4.84	1.24	0.44	155.51
Sample size	4,007	4,007	4,007	4,004

Note: This table reports the coefficient estimates of equation [4], regressing the household composition outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

2.6 Heterogeneous Effects of Peace

The effects of peace would be heterogeneous with individual characteristics. I examine the effects of peace on the specific subgroups with the following model:

$$Y_{it} = \phi_0 Peace_t + \phi_1 Peace_t \times Rural_i + \phi_2 Peace_t \times Group_i + \phi_3 Peace_t \times Rural_i \times Group_i + X_{it}\Gamma + \delta_i + \eta_{it} \qquad [7]$$

where the *Group* represents the group of interest. I primarily consider the individuals under age 30 as young individuals may be more competitive in physical work with brawn, and the individuals in households with a farm as it would be easier for them to find work. The rest of the model is specified the same as equation [4] except for the inclusion of $Peace \times Group$ and $Peace \times Rural \times Group$. The coefficient estimates of the triple interaction term, ϕ_3, capture the group-specific gradients of the effects of peace. Standard errors are clustered on the during-conflict baseline wave community.

The estimates of equation [7] are reported in table 2.11. While we find males under 30 generally work more after the end of the insurgency in panel A, there are no significant group-specific effects of peace. However, for females, we can find that both young females and females in households with a farm have even stronger effects of peace on work. Young females and their brawn would have made them work more during the insurgency, which would lead to the negative coefficient estimate of the young female-specific effects of peace. The females in the households with a farm would have had better access to work, resulting in a more significant decrease in work after the end of the insurgency. I also examined the heterogeneous effects of peace with primary school education and having under 5 children, but I was not able to find any significant effects (see table A6).

2.7 Evolution of the Effects

The identification of the evolution of the effects of peace is essential to optimize policy interventions with peace. Only the Colombian conflict has been studied for the evolution, with no evidence on labor market outcomes (Bernal et al. 2022; Prem et al. 2021b; Prem et al. 2020). The evolution of the effects of peace could be examined using equation [4] with different post-conflict waves. So far, the during-

Table 2.11: Heterogeneous Effects of Peace

	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A: Work (Extensive)				
Peace × Rural	-0.02	-0.12***	-0.03	-0.08***
	(0.02)	(0.03)	(0.02)	(0.03)
Peace × Group	0.10**	0.09***	-0.02	-0.00
	(0.04)	(0.03)	(0.05)	(0.05)
Peace × Rural × Group	-0.03	-0.09**	0.02	-0.12**
	(0.05)	(0.04)	(0.05)	(0.06)
Panel B: Working Hours (Intensive)				
Peace × Rural	1.90	4.64**	1.82	2.38
	(1.53)	(2.17)	(1.70)	(1.71)
Peace × Group	0.79	6.99	-0.23	6.38*
	(1.85)	(4.24)	(2.86)	(3.55)
Peace × Rural × Group	2.92	-5.50	1.44	-3.89
	(2.21)	(4.68)	(3.15)	(3.86)
Panel C: Housework				
Peace × Rural	0.00	0.12***	0.00	0.08**
	(0.01)	(0.03)	(0.01)	(0.03)
Peace × Group	0.01	0.01	-0.00	0.06
	(0.01)	(0.03)	(0.01)	(0.06)
Peace × Rural × Group	-0.01	0.05	0.00	0.05
	(0.01)	(0.04)	(0.01)	(0.07)
Group	Age under 30		Farm HH	

Note: This table reports the coefficient estimates of equation [6], regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, the interaction term between *Peace* and *Rural*, the indicator for the group of interest *Group*, and the interaction term between *Peace*, *Rural*, and *Group* along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

conflict baseline and 2-year follow-up waves are used to identify the short-run effects of peace. For medium- and long-run effects, the 5-year and 10-year follow-up waves can be used instead of the 2-year follow-up wave. One caveat is that the estimates of the medium- and long-run effects would be relatively more influenced by the international aid and policy interventions regarding the Aceh Insurgency and the 2004 Indian Ocean tsunami and earthquake, leading to a different interpretation of the estimates.

Figure 2.5 shows the evolution of the estimated effects of peace. The x-axis indicates the year of the post-conflict follow-up wave used for the estimate. The blue and red lines are for male and female responses to peace with the shaded areas of 5 percent confidence intervals, respectively. Interestingly, the short-run effects of peace in 2 years were not significantly different from the 5-year and 10-year effects of peace. The amount of aid from policy interventions of approximately 40 million US $ for the Aceh Insurgency and 6.4 billion US $ for the 2004 Indian Ocean tsunami and earthquake makes such lack of the evolution of the effects more interesting (Tajima 2010; Masyrafah and McKeon 2008). For example, the Aceh Peace Reintegration Agency (BRA in Indonesian acronym) distributed over 20 million US $ to the villages affected by the insurgency (Morel et al. 2009). The significant short-run effects and no significant dynamics in the evolution even with the international relief may suggest that early interventions may be most effective for post-conflict recovery.

2.8 Conclusion

This paper provides the first evidence on the causal impacts of peace on individual labor market outcomes with a difference-in-differences framework by exploiting the sudden and unexpected end of the Aceh insurgency in Indonesia as a natural experiment. Identifying the effects of peace is important in understanding the changes in

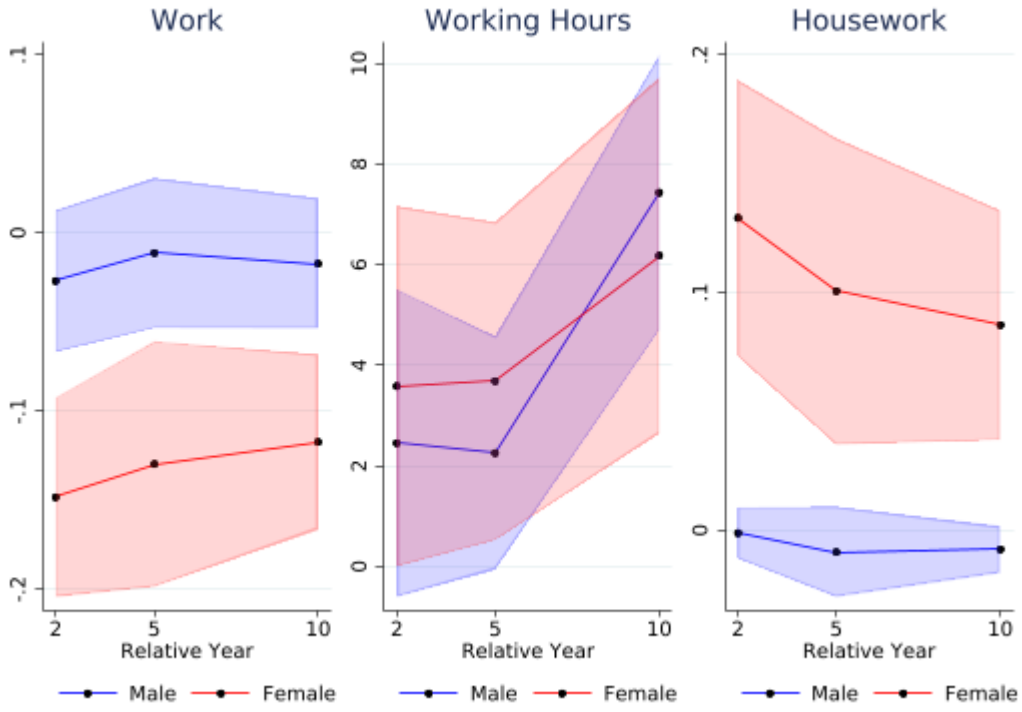

Figure 2.5: Evolution of the Effects of Peace

Note: This figure shows the evolution of the labor market responses to peace over time. The red and blue lines are for the estimated effects of peace for the male and female samples, respectively. The red and blue shaded areas represent the 5 percent confidence intervals. The x-axis indicates the year of the post-conflict follow-up wave used for the estimates, and the y-axis indicates the average value of the variable. The Study of the Tsunami Aftermath and Recovery (STAR) is used for the estimates.

individual welfare after the end of conflicts. As policy interventions are more feasible after the end of the conflict, estimating the effects of peace and its evolution on individual labor market outcomes is essential to design optimal policy interventions.

The end of the Aceh Insurgency significantly reallocated female to male labor market activity in the 2-year short run. The increase in male labor market activity was driven by the decrease in violence after the end of the insurgency. The increase in male labor market activity and the decrease in economic hardship explained the negative effects of peace on female labor market activity. The negative effects of peace

on female labor market activity were stronger for young females and the females in households with a farm, which would be because it may be easier for them to find work with their brawn and farm. The short-run effects of peace in 2 years were not significantly different from the 5-year and 10-year effects of peace.

The study of the effects of peace suggests fruitful areas for future research. As in Prem et al. [2021b], the effects of peace on human capital accumulation and its evolution would shed light on understanding the broader impact of peace. For the long-term post-conflict recovery and economy, rebuilding human capital after the end of conflicts may be more important than rebuilding physical capital. Since there is a paucity of papers on the effects of peace on human capital for the case of *partial* peace in Colombia (Prem et al. 2021b), a study of the effects of complete peace with the end of the Aceh Insurgency would complement the literature.

Chapter 3

Intergenerational Impact of Early Life Exposure to Trauma: Parental Exposure to the Korean War and Risk Aversion

In economics, attitudes and preferences are considered fundamental components of individual characteristics that are not altered in the long run. Short-run changes may occur due to unanticipated shocks, but the changes are likely to be brief, implying that the individual preference traits such as attitudes towards time and risk may be determined at an early age. As recent studies amount evidence on the long-run impact of early life shocks, the question of whether the shock has an even longer-run effect on the next generation naturally follows. However, to the best of our knowledge, there is no study that investigates whether and how the impact of early life shocks passes on to the next generation. In this paper, we fill this gap in the literature by investigating the intergenerational effects of early life shocks on risk preferences.

There is a growing interest in parental influence as an important determinant of preferences. The literature examines intergenerational persistence in preference-related factors including risk preference, time preference, altruism, values, ethics, religious traits, and generosity (Alan et al. 2017; Arrondel 2013; Bisin and Verdier 2000; Wilhelm et al. 2008). The intergenerational persistence of values leads to the transfer of important economic outcomes such as socioeconomic status, female labor force participation, human capital, and saving propensities[1] (Charles and Hurst 2003; Deckers et al. 2015; Fernández et al. 2004). Genetics is one clear reason for

[1]More broadly, culture – values and beliefs transmitted across generation through ethnic, religious, and social groups – affects preferences, labor market participation, and fertility behavior (Fernández and Fogli 2009; Guiso et al. 2006; Schmidt 2008).

intergenerational persistence of preferences and economic decision making (Carpenter et al. 2011 and Cesarini et al. 2010), as values and preference are considered intrinsic qualities determined by genetic factors.

However, economic models suggest that postnatal parental behavior may be an extra, non-genetic channel for the intergenerational transfer through parental effort, and emulation of preferences of parents by children (Becker and Mulligan 1997; Bisin et al. 2004; Carvalho 2012; Doepke and Zilibotti 2008; Grönqvist et al. 2017). Thus, early life shocks to individuals that fundamentally alter preferences may affect the preferences of their children. This implies that traumatic events may not only affect the exposed individuals in the long run, but they may also affect their offspring through postnatal factors.

We study the intergenerational effects of exposure to a major trauma during the sensitive period of development on risk preferences. The 7th wave of the Korean Labor & Income Panel Study provides a unique opportunity to study the intergenerational effects of Korean War exposure during the sensitive development period of age 4 to 8[2]. It is a population-representative longitudinal survey of South Korea with rich individual and household-level information. In particular, the 7th wave includes a set of five hypothetical choice experiments along with detailed relationship information within a household. We use structural and reduced-form estimation methods with difference-in-differences-type analysis where the treatment status is defined by maternal age at exposure and geographic war intensity. We specify the treatment as the children whose mother experienced the Korean War during the sensitive development period and were residing in 'risky' provinces, defined by the provinces with civilian injuries and casualties per capita higher than the national average.

[2]Kim and Lee [2014] show that the respondents who were exposed to the Korean War, a major trauma, between 4-8 years old were more risk averse after more than 5 decades since exposure. We validate the choice of age 4 to 8 sensitive development period in our analysis.

We first replicate Kim and Lee [2014] for the first generation by gender and provide new evidence that the Korean War exposure made only mothers more risk averse with null effects on fathers. We find that the intergenerational effects are negative. Subgroup analysis reveals that only sons are significantly affected. While the effects of the exposure to the Korean War during the sensitive period made the sons of the affected mothers more risk-loving, the exposure made the first-generation mothers more risk-averse.

The mechanism of the opposite effects between mothers and sons is investigated further. We first rule out disassortative mating and differential fertility, as we document no disassortative mating of the first generation and similar sibsize between the treatment and control groups. Then, mother-child gender dyad analysis reveals that only sons are significantly affected. The maternal exposure to the Korean War made the sons more risk-loving, while the mothers were more risk-averse. Given that only sons are significantly affected, the parent-child attachment may be the primary mechanism, as sons tend to rebel against emotionally detached mothers, hence the direction of preference formation would be opposite to the parents (Hoeve et al. 2011). Persistent parental trauma caused by childhood exposure may affect the parent-child relationship (Baranov et al. 2020), consequently affecting the direction or magnitude of value transmission. Negative effects of the Korean War exposure on health capital may as well have deterred parent-child attachment. Further, the opposite effects of the Korean War exposure on risk preferences for the traumatized parents suggest that nurture is an important determining factor of risk attitude, isolated from genetic factors.

The parent-child attachment mechanism is consistent with the psychology literature on intergenerational effects of parental distress, the literature that examines how traumatic experiences by parents are passed on to the next generation. Studies

of the Holocaust survivors and refugees show that parental trauma affects parent-child interaction through insecure attachment and reduced availability. In general, the stress from negative life events is identified as a negative factor in parent-child attachment (Enlow et al. 2014; Horesh et al. 2014; Mercer et al. 1986; Schwerdtfeger and Goff 2007; Van Ee et al. 2016). Hoeve et al. [2011] find that delinquency increased by neglectful parenting for males. The literature suggests that the detachment from children due to war exposure may adversely affect the mother-son dyad most. Mental health issues of mothers have been suggested to be correlated to worse socio-emotional development of their male offspring (Baranov et al. 2020). Additionally, we directly document that the Korean War exposure increased the first generation's disabilities, as parental health capital may negatively affect attachment to the children.

The main contributions of this paper are threefold. First, this is the first paper to show that the experience of a traumatic event during the sensitive development period has an intergenerational impact on their offspring. Exposures to traumatic events such as natural disasters alter the risk preferences of adult subjects in several experimental studies (Cassar et al. 2017; Eckel et al. 2009; Li et al. 2011; Sacco et al. 2003). Trauma experiences of war violence, forced labor, and financial distress modify the risk attitudes of affected individuals in the long run (Bellows and Miguel 2009; Callen et al. 2014; Malmendier and Nagel 2011; Nikolova et al. 2022). Kim and Lee [2014] find that the respondents who experienced a major civil war, the Korean War, during childhood are more risk-averse after approximately five decades. They identify a critical age range that leaves a lasting influence on risk attitude, related to the sensitive development period of risk preference formation. Showing the negative intergenerational effects of the Korean War, the findings of this paper indicate that experience of major trauma may have intergenerational effects on preferences.

Second, we find a significant influence of non-genetic factors in preference formation. The positive transmission of value and attitude across generations is the result of both genetic and postnatal factors. However, the opposite effects of the Korean War exposure between the first and second generations imply that non-genetic factors dominate genetic factors in attitude formation, as the direction of genetic transfer would undeniably be positive. We find that the mothers who are more risk-averse because of the exposure to trauma have more risk-loving sons. The evidence suggests that nurture is a determining factor in risk attitude formation, confirming economic models that predict a significant environmental impact on attitude formation (Becker and Mulligan 1997; Black et al. 2017; Bisin et al. 2004; Doepke and Zilibotti 2008). This also adds to the literature that studies the intergenerational transfer of risk preferences (Alan et al. 2017; Brown and Van der Pol 2015; Hryshko et al. 2011; Necker and Voskort 2014; De Paola 2013).

Third, we examine the mechanisms of the negative effects. Why are the risk preferences of mothers and sons affected in the opposite direction by the Korean War exposure? Seminal works by Dohmen et al. [2012] and Chowdhury et al. [2022] find positive risk attitude transmission in developed and developing countries, respectively. We first investigate assortative mating, as Dohmen et al. [2012] identify assortative mating as the mechanism for the positive transmission of risk preferences from parents to children. The analysis reveals that the affected mothers do not display disassortative mating behavior, not seeking spouses with more risk-loving preferences. As an alternative, the deficiency in parent-child attachment is suggested as the mechanism, following the household production model by Cobb-Clark et al. [2019], which indicates that parenting style is a significant component of parental investment in human development. Chowdhury et al. [2022] also exhaust assortative mating, parenting style effect, sibling effect, and peer effect, to suggest that genetic

factors dominate the positive transmission of risk attitude.

The rest of the paper is organized as follows. The next section provides background about Korean War and the dataset. Then section 2 discusses methodology. Section 3 presents and discusses the results. Section 4 concludes the paper.

3.1 Context and Data

3.1.1 The Korean War

Considering strong parent-child similarities in attitude and preferences, pre-war parental selection into different geographic locations based on their risk attitude may have been unlikely but possible. However, the unexpected breakout and plausibly exogenous distribution of war intensity due to rapid and frequent changes in geographic frontline make the war a natural experiment, a great set-up to examine the causal impact of the war. First, the breakout was unanticipated as shown by the unpreparedness of South Korea. On a Sunday morning, June 25th, 1950 at 4 AM, North Korea invaded South Korea without a declaration of war. South Korean troops were on leave from Saturday morning until Sunday evening. As such, the majority of South Korean soldiers were at home sleeping at the breakout of the war, highlighting the unexpectedness of the War.

As well, the pace in the early stages was rapid, and South Korea almost lost control over the entire country within the first two months, which makes the geographic war intensity arbitrary (see figure 1). Although North Korean troops advanced using the Seoul-Busan line, from Northwest (Seoul) to Southeast (Gyeongsangnamdo). This is a typical pattern that occurred in the past, for example, in Imjin War, a major Japanese invasion in 1592. The two biggest cities and centers of population are

connected by the Seoul-Busan axis and the mountain range pattern of South Korea naturally leads the invaders to use the axis for occupation. However, the highest civilian casualties were in Gangwondo and Jeollandmdo, the opposite corners of the axis. In Gangwondo, the 8th and the 6th Maneuver Divisions maintained the frontline longer than the other Divisions, hence the battle was prolonged in the province. Although little advance was made in Jeollanamdo, the North Korean Partisan exploited mountain regions of the province to cause greater civilian damage.

In the counteroffensive following the UN allied forces' reinforcement to Busan, the allied forces arranged landing operations in September 1950. This counteroffensive was based on a strategic decision to split the territories controlled by North Korea, rather than what would have been a traditional military decision to push back the frontline. As such, in the counteroffensive, they skipped the middle part of the nation and directly executed a landing operation in the port city of Incheon in Gyeonggido, an operation known as Operation Chromite.

As a result, the distribution of geographic war intensity seems arbitrarily dispersed across provinces[3] (see figure 1) because the varying intensity by region was a result of contemporaneous battle strategies that may have been impossible to predict. Consistently, provinces with high civilian war casualties are geographically haphazard. Therefore, it would have been impossible for households to make prewar geographic selections by risk attitudes. This allows us to make causal inferences, exploiting within-cohort variation in geographic treatment intensity.

One unique feature of the war is that the civilian casualty is heavily isolated in the year 1950, which makes the war ideal to identify the age at exposure to the war.

[3]Ideally, we would want to exploit finer spatial variation. However, the spatial distribution of war intensity is only available at the province level. Such a province-level classification would include unaffected individuals into the treatment group, which would bias the intergenerational effects of the Korean War exposure toward zero assuming the decreasing marginal treatment effects with the war intensity.

The North almost entirely occupied South Korea by September 1950, except for the port city of Busan at the Southern end of the Korean peninsula. However, following the reinforcement by the UN troops led by the US, the allied forces successfully retaliated. In two months by November 1950, almost entire North Korea was now occupied by the allied forces. Then, following the Chinese intervention, the front of the war was pushed back to near the original border and the stalemate, where most casualties were military personnel, continued until the end of the war. As such, the age in the year 1950 is defined as the age of exposure in the analysis.

3.1.2 Korean Labor and Income Panel Study

We use the 7th wave of the Korean Labor and Income Panel Study (KLIPS), a population-representative longitudinal survey of approximately 5,000 households. The 7th wave of the survey was conducted in 2004 and includes a set of five hypothetical choice experiments. Estimated risk aversion from the responses to these questions accurately predicts economic behaviors that are related to risk attitude, such as stock market participation and self-employment (Kim et al. 2012). The survey is conducted 51 years after the end of the war; hence it is suitable for the analysis of the very long run, intergenerational effects of the Korean War exposure on risk preferences.

Table 3.1 presents descriptive statistics[4]. Columns (1) and (2) show the mean and standard deviations for the entire sample, and columns (3) to (6) report the mean of the sample stratified by maternal age and the province of birth. The sensitive age indicator $mage^{4-8}$ is equal to one if the mother was between 4- to 8-year-old in 1950,

[4]KLIPS reports detailed relationships among each member within each household. This intra-household relationship information enables us to identify the treatment group by parental age and province. The 7th wave includes 11,661 individuals from 4,762 households. For our analysis, we include adult respondents, 18 or older, who were less than 50 years old – those who were born after the end of the war. We exclude samples with missing variables such as parental characteristics. The final sample contains 3,062 respondents.

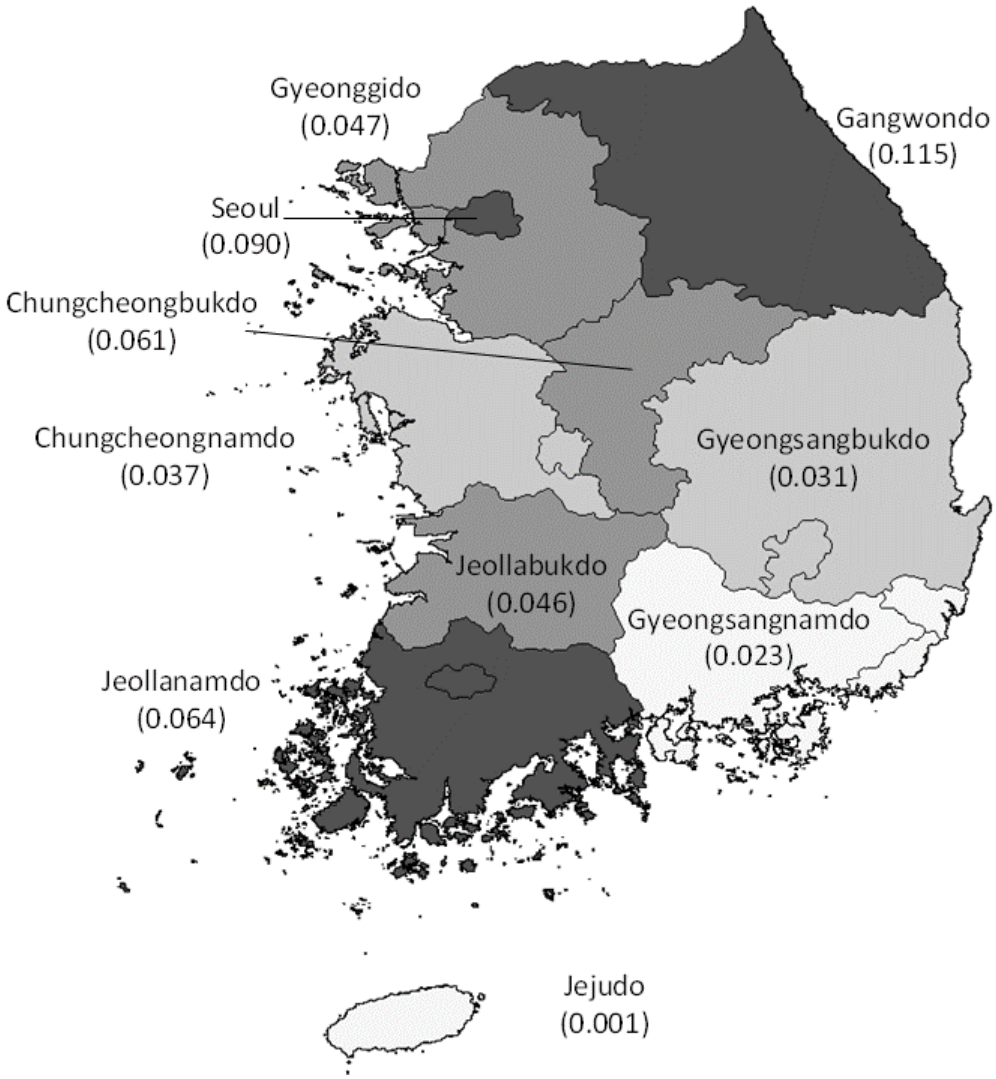

Figure 3.1: Injuries and Casualties from the Korean War per Population by Province

Source: Population data from the 1949 Census of South Korea. War damage data has been obtained from Kim [1996], p.85.
Note: Number of province-level civilian injury/casualties per population ratios are shown in parenthesis. The data is only available at the province-level.

at the peak of the war. The war intensity indicator $RArea^m$ is equal to one if the mother resided in provinces with civilian injuries/casualties greater than the national average of 0.051. Thus, column (3) becomes the treatment group, the offspring whose mother experienced the Korean War between 4- to 8-year-old, and columns (4) to (6) are the control groups. Column (7) shows raw difference-in-differences-type estimates

with their significance levels. In panel A, the proportion of safe choices, or more risk-averse choices[5] is significantly lower in column (3). Panel B presents the indicator variables used for the analysis. Individual covariates are reported in panel C, and the insignificant difference-in-differences in column (7) support that the Korean War exposure is a natural experiment, except for the marginal significance for marital status. The average individual in the sample is a single male in his mid-20s with a high school degree.

3.2 Methodology

The 7th wave of KLIPS includes a set of five hypothetical lottery choice experiments. Respondents are asked to choose between the two options as a payoff for a day's work. Option A provides a certain payoff of 100,000 Korean won (KRW) and option B provides a lottery, instead of the certainty payment. For example, for question 1, the respondents choose between getting paid KRW 100,000 or a lottery that pays KRW 150,000 with the probability of 0.5 and KRW 50,000 with a probability of 0.5. Table 3.2 summarizes the choices given by each question[6]. Using the responses to the five choices, we estimate the risk aversion parameter using structural estimation.

First, we estimate the risk aversion parameter γ assuming a constant relative risk

[5]See table 3.2 for a detailed description.

[6]The distributions of each choice experiment could be found in figure A4.

Table 3.1: Hypothetical lottery choice experiments

Question Number	Option A (Safe Choice)	Option B (Risky Choice)	Gap in Expected Payoff (Option A - Option B)
1	100,000	1/2 of 150,000, 1/2 of 50,000	0
2	100,000	1/2 of 200,000, 1/2 of 0	0
3	100,000	2/5 of 200,000, 3/5 of 0	20,000
4	100,000	3/5 of 200,000, 2/5 of 0	-20,000
5	100,000	1/5 of 500,000, 4/5 of 0	0

Source: Kim et al. [2012].
Note: This table shows all five hypothetical lottery choice experiments in the 7th wave of KLIPS. All units are in KRW; KRW 100,000 is equivalent to USD 105.12, based on the average exchange rate in 2004, or equivalent to 0.6% of annual GDP per capita of South Korea in 2004. The questions were asked in the order of the question number. Each question was asked for the payment option for a day's work.

Table 3.2: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mother Sensitive Age	Entire Sample		Yes	Yes	No	No	DID
Mother Risky War Area	Mean	Std. Dev.	Yes	No	Yes	No	
Panel A. Outcome variable							
Proportion of safe choices	0.84	0.31	0.76	0.85	0.83	0.84	-0.08*
Panel B. Treatment variable							
$mage^{4-8}$	0.11	0.32	1.00	1.00	0.00	0.00	-
$RArea^{m}$	0.31	0.46	1.00	0.00	1.00	0.00	-
Panel C. Individual Characteristic							
Male	0.57	0.50	0.68	0.61	0.55	0.56	0.09
Age at survey year (2004)	27.18	7.02	31.16	31.17	26.16	26.89	0.73
High school graduates	0.90	0.30	0.95	0.95	0.90	0.89	-0.00
College graduates	0.38	0.49	0.55	0.58	0.33	0.37	0.01
Married	0.17	0.38	0.32	0.25	0.14	0.17	0.11*
Household income (inverse hyperbolic transformation)	3.92	0.96	3.73	3.74	3.96	3.94	-0.03
Sibsize	2.67	1.41	2.95	2.99	2.59	2.65	0.02
Sample Size	3,062		133	234	784	1,911	

Note: This table shows the mean and standard deviation of the entire sample in columns (1) and (2). Columns (3)-(6) report the averages of the subsamples stratified by Mother Sensitive Age and Mother Risky War Area indicators. In column (7), we report the difference-in-differences estimate with each covariate as dependent variable. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

aversion (CRRA) utility function[7]:

$$U(x) = \frac{x^{(1-\gamma)}}{1-\gamma} \qquad [1]$$

Then, we include a structural noise parameter μ, as in Luce [1959] and Holt and Laury [2002]. The expected utility of option j is denoted as A (risk-free cash) or B (lottery). The noise parameter μ captures the insensitivity of choice probabilities to payoffs, in the following probabilistic choice index in the form of a cumulative probability distribution function (Andersen et al. 2008):

$$\Delta EU = \frac{EU_B^{1/\mu}}{EU_A^{1/\mu} + EU_B^{1/\mu}} \qquad [2]$$

The noise parameter captures randomness in choices made by respondents. The choice probability approaches 0.5 (fully random) as μ increases and the choice becomes increasingly inconsistent with the expected utility theory, that is, as μ approaches infinite, the choice becomes completely random. On the other hand, the probability of choosing the option with greater expected utility approaches one as μ approaches zero.

Utilizing the five responses to the set of hypothetical choice experiments, we construct the following conditional log-likelihood:

$$lnL(\gamma, \mu; y, X) = \sum_i^N \sum_j^5 [(ln(\Delta EU)|y_i^j = 1) + (ln(1 - \Delta EU)|y_i^j = -1)] \qquad [3]$$

[7]The power-expo utility function is more flexible (Saha 1993), $U(x) = \frac{1-exp(-\alpha x^{1-\gamma})}{\alpha}$. This function reduces to CRRA when $\alpha = 0$ and to CARA when $\gamma = 0$. Using the power-expo utility function for the KLIPS data, Kim et al. [2012] shows that the parameter α is statistically insignificant. The result is consistent with the intuition, as α measures the responses to the modification in payoff amount. However, the hypothetical choice experiments from KLIPS do not seem to display sufficient variations in the payoff amount (see table 3.2).

where i represents the individual and j represents the choice experiment. $y_i^j = 1$ (or -1) means that individual i chose option A (or B) for the jth choice experiment. The risk aversion parameter γ and structural noise parameter μ are estimated while allowing heterogeneity of the parameters, linearly depending on individual characteristics X[8]. The individual heterogeneity of interest is the treatment indicator, based on maternal exposure to the Korean War. The treatment group, therefore, includes the respondents whose mother was exposed to the war during the sensitive age of 4-8, as shown by our replication of Kim and Lee [2014] using the same dataset in table A7[9]. X includes the indicator for temporal variation for mothers between 4 and 8 at the peak of the war, the indicator for province-level spatial variation for war intensity above the national average, and the treatment indicator as the interaction of the temporal and spatial variations. For controls, we only include gender and age only, as other covariates are potentially endogenous to the treatment.

3.3 Results and Discussions

3.3.1 Main Analysis: Structural Estimation of Risk Parameters

Table 3.3 presents the structural estimation of the CRRA risk parameter γ as a function of individual characteristics. Column (1) reports the result of the baseline model with age and gender, and column (2) reports the results controlling for gender, age, and education. Column (1) shows that respondents whose mothers experienced

[8]Maximum likelihood estimation was performed using Stata's ml command. The wild bootstrapped p-values are clustered at birth province level (Kline and Santos 2012)

[9]They estimate structural risk parameters, like equation [3], and show that respondents who experienced the war during 4-8 remained more risk averse in the long run among all stratified age groups. The treatment group was similarly defined by the interaction between the age in 1950 and war intensity.

the war during the sensitive development period exhibited significant decreases in risk aversion, and the estimates are stable even when we additionally control for education in column (2). Results presented in column (1) show that the coefficient estimate of maternal exposure amounts to 26 percent of the baseline risk parameter 0.80.

Table 3.3: Maximum likelihood estimations of risk parameter and noise parameter

	Baseline	
	(1)	(2)
Risk preference parameter		
$mage^{4-8} \times RArea^{m}$	-0.21**	-0.23**
	(0.04)	(0.05)
$mage^{4-8}$	0.01	0.02
	(0.86)	(0.76)
$RArea^{m}$	-0.03	-0.02
	(0.70)	(0.71)
Constant	0.80***	0.90***
	(0.00)	(0.00)
Controls	Male, Age	+ Education
Number of observations	3,062	3,062

Note: This table reports the baseline structural coefficient estimates of equation [3] using (Holt and Laury 2002). Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

The results suggest that the Korean War exposure made the offspring more risk-loving. The mothers who experienced civil war at an early age are more risk-averse than the individuals who do not (see table A7), and the offspring of the affected mothers are statistically more risk-loving than the individuals whose mothers are not exposed to the trauma during the sensitive age. Trauma during the sensitive development period does not only affect the risk aversion of the affected females in the long-run, but it may also affect the risk preferences of the next generation even in the longer-run. The positive intergenerational effects on risk preferences are in contrast with the positive correlation in parent-child preferences in the general population (Dohmen et al. 2012).

The intergenerational impact of risk preferences is mostly limited to the parents who experienced the war during the specific age group, as identified in the literature. Table 3.4 shows the risk parameter γ for different age groups. We estimate the parameter using a fully specified model as in column (2) of table 3.3 and define the 'sensitive age' differently in each column. Estimated parameters reported in columns (1), (2), and (4) represent the risk attitudes of respondents whose parents were in utero – age 0, age 1–3, and age 9–13 at the peak of the war, respectively. The results for utero – age 0 and age 1–3 show that risk preferences are not different from the respective control groups, as the parents' risk preferences are not either. While the estimate for maternal exposure in column (4) is marginally significant, the exposure between 9 and 13 did not significantly affect the mother's risk preferences when we replicated Kim and Lee [2014] in table A7[10]. It is intriguing that risk preferences were not affected by father's exposure even for the 4–8 age group when we additionally include paternal exposure as placebo checks (see table A8). The evidence is consistent with the first-generation results in table A7. Having mothers experiencing the war during the sensitive age period has a negative intergenerational impact on the risk preferences of their offspring.

3.3.2 Robustness Checks

As a corroborative analysis, we perform two robustness checks. First, we exclude all the "movers" from the sample. The dataset provides birthplace and residence at the age of 14 at the provincial level. In the main analysis, we use the mother's birthplace information to determine the treatment group. For example, if a respondent's mother

[10]We replicated the Kim and Lee (2014) with two different samples. First, we examined the sample of age 20-85, the same as Kim and Lee [2014], by gender in columns (1) and (2). However, the wide age range naturally includes the second generation. Therefore, in the second sample in columns (3) and (4), we include the individuals of age 50-85 to exclude the second generation.

Table 3.4: Estimation of risk parameter using different age groups

	(1)	(2)	(3)	(4)
Risk preference parameter				
$mage^{inutero-0} \times RArea^m$	0.18			
	(0.39)			
$mage^{1-3} \times RArea^m$		0.07		
		(0.61)		
$mage^{4-8} \times RArea^m$			-0.21**	
			(0.04)	
$mage^{9-13} \times RArea^m$				0.23*
				(0.05)
Number of observations	3,062	3,062	3,062	3,062

Note: This table reports the structural coefficient estimates of equation [3] using (Holt and Laury 2002) with alternative sensitive age groups as in Kim and Lee [2014]. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

was between 4 and 8 in 1950 and resided in one of the provinces defined as the risky area, the respondent is in the treatment group. However, for the mothers whose birthplace and residence at age 14 are different, the place of residence during the war is more likely to be inaccurate. Therefore, we define the "movers" as the ones whose birthplace and residence at age 14 are different and exclude all the respondents whose mothers were movers.

Second, we include the respondents whose parental information is missing in the control group. The inclusion would lead to an estimate of the partial impact of the war, as some of the parents whose data is missing may have to be included in the treatment group. By including the sample with missing parental information, the estimates would provide an underestimate but speak to the validity of our results for the general South Korean population.

Table 3.5 reports the structural risk parameter γ for the interaction terms between the sensitive age and risky area for the corroborative analysis. The top row uses the indicator variable, $RArea^m$, to control for the geographic variation in war intensity while the bottom row uses the continuous variable $Intensity^m$, the provincial injuries

and casualties per population for father and mother. Columns (1) and (2) are the baseline model, and the results presented in column (1) are from column (2) of table 3.3. Columns (3) and (4) exclude the respondents whose mother's place of birth is different from the residence at age 14. In columns (5) and (6), we include respondents whose parental data is missing. The results reported in table 3.5 show that the estimation is robust to the use of continuous war intensity variable, exclusion of movers, and relaxing sample restrictions. As in columns (1) and (2), parameters shown in columns (3) – (6) suggest that the intergenerational effects of the Korean War exposure made the offspring more risk-loving.

Table 3.5: Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)
Risk preference parameter						
$mage^{4-8} \times RArea^{m}$	-0.21**		-0.19*		-0.22**	
	(0.04)		(0.06)		(0.04)	
$mage^{4-8} \times Intensity^{m}$		-2.58**		-2.54**		-2.51**
		(0.04)		(0.04)		(0.03)
Sample	Basline		No migrant parents of treatment group		Including no parents info as control	
Number of observations	3,062	3,062	2,646	2,646	6,841	6,841

Note: This table reports the structural coefficient estimates of equation [3] using (Holt and Laury 2002) with alternative sample specifications. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

As a supplementary analysis, we also conduct the analogous reduced-form estimation:

$$Safechoice_i = \alpha_1 mage_i^{4-8} + \alpha_2 RArea_i^m + \alpha_3 mage_i^{4-8} \times RArea_i^m + X_i'\Gamma + \delta_{province} + \epsilon_i \qquad [4]$$

where i denotes individual, $mage_i^{4-8}$ is the indicator for the maternal age of 4-8 at the peak of the war, $RArea_i^m$ is the indicator for mother's residency in the risky area

during the war. $\delta_{province}$ represents the province fixed effect. The dependent variable is the number of certainty option A, out of five hypothetical choice experiments, normalized to 1. For example, if the respondent selected 4 option A's and 1 option B, the dependent variable takes the value of 0.8. The coefficient of the interaction term, α_3, would represent the intergenerational effects of maternal war exposure on risk preferences. We also perform the identical analysis but replace the "risky area" indicator variable $RArea^m$ with the continuous measure of provincial injuries and casualties $Intensity_i^m$:

$$Safechoice_i = \delta_1 mage_i^{4-8} + \delta_2 Intensity_i^m + \delta_3 mage_i^{4-8} \times Intensity_i^m + X_i'\Gamma + \delta_{province} + \epsilon_i \qquad [5]$$

where $Intensity_i^m$ represents the civilian injuries and casualty for the mother's province of birth.

Table 3.6 presents the results of the reduced-formed form equations (4) and (5), where the number of certainty options chosen by the respondent is the dependent variable[11]. The odd-numbered columns report the estimated coefficient α_3, and the even-numbered columns report δ_3 estimates. The first two columns are the baseline model, the next columns exclude movers, and the last two columns additionally include the individuals with missing parents' information as a part of the control group. The results are qualitatively comparable to the results from the main structural analysis. While the mothers are more risk-averse, the children are not more risk-averse than the control groups. The weak statistical significance is not surprising as the reduced-form analysis does not consider noises in responses.

[11]There may be concerns about the validity of the proportion of safe choices as a measure of risk preferences since choice experiments 3 and 4 involve different expected returns between safe and lottery choices. We resolve the issue by using the proportion of safe choices excluding choice experiments 3 and 4 in table A9. It is reassuring to find the qualitatively same results.

Table 3.6: Reduced-form estimates

	(1)	(2)	(3)	(4)	(5)	(6)
$mage^{4-8} \times RArea^m$	-0.07*		-0.05		-0.07*	
	(0.07)		(0.22)		(0.08)	
$mage^{4-8} \times Intensity^m$		-0.73		-0.56		-0.70
		(0.13)		(0.28)		(0.12)
Sample	Basline		No migrant parents of treatment group		Including no parents info as control	
Number of observations	3,062	3,062	2,646	2,646	6,841	6,841

Note: This table reports estimated α_3 from reduced-form equation [4], and estimated δ_3 from reduced-form equation [5]. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

3.3.3 Potential Mechanisms

Several literature report detachments and neglecting parenting style of trauma survivors (Enlow et al. 2014; Horesh et al. 2014; Schwerdtfeger and Goff 2007; Van Ee et al. 2016). For the traumatized war victims, this may engender rebellious behavior in the children. Instead of emulating their parents' values and preferences, these children may be disaffected and strive for the opposite values and preferences. Hoeve et al. [2011] shows that neglectful parenting was associated with higher levels of delinquency in males only. Mental health issues of mothers have been suggested to be correlated with poor socio-emotional development of their male offspring (Baranov et al. 2020).

Parents-offspring dyad analysis may be effective in identifying potential mechanisms because the lack of parent-child attachment may be a channel of negative transmission, and according to the literature, detachment may have the greatest impact on preferences formation in the mother-son dyad. In the specific Korean context, child-rearing has heavily fallen upon mothers until the 1980s' Korean society. Therefore, we estimate the parameters and coefficients for the structural equation [3] and the reduced-form equation [4] for mother-son and mother-daughter dyads. That is,

a mother's exposure to war variables would be further split into son and daughter interaction terms.

The results of the parent-offspring dyad analysis in table 3.7 are consistent with the intuition. Columns (1) and (2) report the structural risk aversion parameters for the triple interaction terms for war exposure at the sensitive age, risky area, and the indicator variable for the sex of respondents. Similarly, columns (3) and (4) report the triple difference estimators from the reduced-form equation [4]. Sons have a significant negative risk preferences impact, while daughters were insignificantly affected. Sons with the mother who experienced the war during the sensitive age period are more risk-loving. This may suggest that the mechanism behind the negative effects on risk preferences is the detached parenting style due to trauma. As literature and the result imply, a less attached, neglectful parenting style may instigate more rebellious behavior from children, who may opt not to emulate values and preferences displayed by their parents (Baranov et al. 2020; Hoeve et al. 2011). It is reassuring that we found null effects when the indicators for paternal exposure by son and daughter are additionally included in the model (see table A10).

Physical health may be a crucial factor that impedes parent-child attachment formation. Due to the limited number of observations and health-related variables, KLIPS is not fitting to investigate physical disabilities and the war exposure of the parents. As such, we examine the relationship between parental war exposure and their physical disability using the reduced-form equation [4] with the complete 2010 Korean Census provided by MicroData Integrated Service (MDIS) of Statistics Korea. This private dataset provides 639,109 samples for the 1936-1951 birth cohorts who experienced the Korean War, the cohorts born within five years before and after the treatment group. The complete Census provides birthplace information, as well as difficulties in sensory, physical, and daily activities. We replace the dependent

Table 3.7: Estimation of risk parameters and reduced-form DID coefficients for parents-offspring dyads

	Structural estimate		Reduced-form estimate	
	(1)	(2)	(3)	(4)
$mage^{4-8} \times RArea^{m} \times Male$	-0.28*	-0.25*	-0.10**	-0.08
	(0.06)	(0.08)	(0.05)	(0.18)
$mage^{4-8} \times RArea^{m} \times Female$	-0.13	-0.12	-0.00	0.01
	(0.20)	(0.30)	(0.98)	(0.86)
Sample	Baseline	No mover	Baseline	No mover
R squared	-	-	0.07	0.06
Number of observations	3,062	2,646	3,062	2,646

Note: Columns (1) and (2) reports the estimated structural risk aversion parameter of triple interaction term of the indicator variable for each parent-offspring dyad. Columns (3) and (4) report reduced-form DID estimates for each parent-offspring dyad. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

variable from the reduced-form equations above with the indicator variables for four different difficulty measures[12] and examine if the mothers of the treatment group may be more challenged in tasks that are likely to have exacerbated the attachment to the children, provided that difficulty prevalence are positively correlated between when children were young and in the Census year.

Considering the positive correlation between contemporaneous physical disabilities and past health level, table 3.8 shows that the parents and especially mothers of the treatment group are more likely to have a physical disability. Panel A shows that the individuals who were the parents of the treatment group are more prone to sensory, movement, and daily difficulty measures, and they are less inclined to have no difficulties. The subgroup analysis by sex in panel B shows stronger results for the females. These parents, especially mothers, may be physically challenged to form an attachment to their children in the treatment group.

Next, we investigate assortative mating as an alternative mechanism of the negative intergenerational effects on risk preferences. For the general population, the positive correlation of risk preferences between parents and offspring– where more risk-averse parents would have more risk-averse children –is explained by assortative mating (Dohmen et al. 2012). More risk-averse individuals tend to mate with more risk-averse partners to produce children. In turn, having more risk-averse parents increases the risk aversion for these children through genetic and environmental factors. We investigate if the opposite effects on risk preferences between the mothers and sons are similarly driven by a disassortative mating. In other words, we test if more risk-averse mothers with the war exposure select a partner who is more risk-loving

[12]The difficulty measures include sensory difficulty (visual, auditory, and language disability), movement difficulty (walking and climbing the stairs), daily difficulty (difficulties in performing regular daily tasks such as going to the market and health clinics), and no difficulty (having no difficulties of any kind).

Table 3.8: Parents of treatment group and difficulties in life

Dependent Variable	Sensory Difficulty (1)	Physical Difficulty (2)	Daily Difficulty (3)	No Difficulty (4)
Panel A. Baseline				
$age^{4-8} \times RArea$	0.03**	0.14***	0.02**	-0.17***
	(0.01)	(0.00)	(0.00)	(0.00)
Panel B. Gender heterogeneity				
$age^{4-8} \times RArea \times Male$	0.024	0.081**	0.02**	-0.13***
	(0.08)	(0.01)	(0.00)	(0.00)
$age^{4-8} \times RArea \times Female$	0.035***	0.19***	0.02*	-0.20***
	(0.00)	(0.00)	(0.06)	(0.00)
Number of observations	639,109	639,109	639,109	639,109

Note: This table reports estimated gender-specific α_3 from reduced-form equation [4] with difficulties as outcome variables. The 2010 Korean Census data is used for the results. P-values in parentheses, which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

and this, in turn, could contribute to the opposite effects of the Korean War exposure between mothers and sons.

The following reduced-form analysis examines if disassortative mating occurs for the war-exposed mothers:

$$Safechoice_i^{Spouse} = \beta_1 age_i^{4-8} + \beta_2 RArea_i + \beta_3 age_i^{4-8} \times RArea_i + X_i'\Gamma + \delta_{province} + \epsilon_i \qquad [6]$$

where i denotes individual, age_i^{4-8} is the indicator for sensitive age exposure, $RArea_i$ represents the indicator of the risky area. $\delta_{province}$ denotes the province fixed effect. The dependent variable is the number of certainty option chosen by the spouse out of five hypothetical choice experiments, normalized to 1. We expect the coefficient β_3 to be negative if these mothers display disassortative mating in risk attitudes.

Table 3.9 presents estimated β_3 from equation [6]. Column (1) utilizes the risky area indicator variable, $RArea$, while column (2) uses the continuous measure of war intensity. Both columns display insignificant relationships between the number

of safe options for spouses, suggesting neither assortative nor disassortative mating. Therefore, disassortative mating would not be a plausible mechanism for the negative intergenerational impact on risk attitude.

Table 3.9: Assortative mating analysis

	(1)	(2)
Wife exposed to war at age 4-8 × Risky Area	-0.01	
	(0.79)	
Wife exposed to war at age 4-8 × Intensity		-0.25
		(0.28)
R squared	0.05	0.05
Number of observations	3,247	3,247

Note: This table reports estimated β_3 from reduced-form equation [6]. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

We perform an auxiliary reduced-form analysis to examine the risk attitude correlation between generations. We estimate the correlation between the number of safe choices made by the mother and the children, and compare the correlation between the treatment group and the control group:

$$Safechoice_i^{children} = \beta Safechoice_i^{mother} + X_i'\Gamma + \delta_{province} + \epsilon_i \qquad [7]$$

where i denotes individual, $Safechoice$ represents the number of certainty options as in equation [4], and superscripts children and mother indicate the respondent and the mother.

The correlation between the number of safe choices by mothers and children, the estimates of the key coefficient β from the reduced-form equation [7], are reported in table 3.10. It shows that β is positive and statistically significant for the control group. One unit increase in the mother's number of safe choices is correlated with the increase in 0.38 safe choices for the children, suggesting a positive correlation between the risk preferences for the control group. For the treatment group, however,

the correlation is smaller. While the lack of a significant difference between the two groups may be due to the small sample size and large standard errors of the treatment group, the difference in magnitudes is substantial. Note that the analysis in table 3.10 requires choice experiment responses for both mother and offspring, which results in a smaller sample size than in table 3.3.

Table 3.10: Correlation between the number of safe choices by parents and children

	(1)	(2)
Mother's number of safe choices	0.26	0.38***
	(0.16)	(0.00)
Sample	Treatment Group	Control Group
Number of observations	70	2,211

Note: This table reports estimated β from reduced-form equation [7]. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Other potential mechanisms would be differential resource availability, fertility, and selection by treatment status. If the treatment group had more investment and resources while they were growing up, their preferences could be formed differently. A more risk-loving second generation implies that the second generation would be wealthier and have a smaller number of siblings. Current wealth and sibling size could be a proxy for childhood investment and differential fertility. Using a reduced-form method as in equation [4], table 3.11 shows that there are no differences in present wealth for both mother and offspring and sibling size by the treatment. In addition, we find no evidence for the selection of parental information for the treatment status by examining the current cohabiting status in column (4).

Using a reduced-form analysis as in equation [4], we test if the treatment group is different in a risk-related behavior, self-employment. Replacing the dependent variable with the indicator variables for whether the individual is currently self-employed or was ever self-employed, the impact of maternal exposure to the Korean War on the

Table 3.11: Wealth and sibling size

Dependent	Wealth	Wealth	Sibsize	Cohabiting with Mother
	(1)	(2)	(3)	(4)
$age^{4-8} \times RArea$	3078.97			
	(0.78)			
$mage^{4-8} \times RArea^m$		772.09	-0.09	0.07
		(0.84)	(0.73)	(0.26)
Sample	Mother	Offspring	Offspring	Offspring
Number of observations	1,544	3,029	2,824	3,062

Note: This table reports estimated β_3 from reduced-form equation [4] with the wealth of the mother, wealth, sibsize, and cohabiting with the mother as outcome variables. While column (1) takes the wealth of the mother as the outcome variable, columns (2)-(4) take the offspring's wealth, sibsize, and cohabiting with the mother as outcome variables. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

offspring's self-employment is estimated. If the transmission is negative, the offspring of more risk-averse parents would be more or equally likely to be self-employed than the control group. The KLIPS reports contemporaneous self-employment status, and we can construct a variable for whether the respondent was ever self-employed at any of the KLIPS waves. More risk-averse individuals would be less likely to be self-employed, and the coefficients for the interaction terms would therefore be negative. Table A11 shows that the estimated coefficients are positive for sons while the estimates are negative for females, although no coefficient estimate is statistically significant. The results are behaviorally consistent with the earlier results. The lack of statistical significance and mixed results may be driven by the low proportion of self-employed individuals in the treatment group[13].

[13]The sample is 25-59 at the time of the survey, and their probability of self-employment were 24%, and 15%, respectively for male and female.

3.4 Conclusion

Risk is pervasive in economic decision-making. As such, risk preferences have a profound effect on economic and behavioral decision-making. Existing literature provides evidence that traumatic experience may have a substantial impact on preference formation, including the risk attitude. This paper investigates whether the traumatic experience during the sensitive development period, known to alter risk preferences in the long run, may also affect the risk preferences of the subsequent generation. We find that the trauma may affect the risk preferences for an even longer-term, by affecting the risk preferences of the subsequent generation. We also find that the direction of the effects is the opposite between the trauma-exposed mothers and their sons. Analysis of the potential mechanisms reveal that the respondents who experienced the war still does not show disassortative mating behavior with no change in fertility. Parent-offspring dyad analysis suggests that the negative intergenerational impacts on risk preferences may be driven by emotional detachment and parenting style. As well, the negative effects on parents' health capital would deter the parent-child attachment formation.

The results of this paper may have an extensive impact on the development and rebuilding of countries that experience major civil conflicts. As a more risk-averse population who experience the war firsthand may be more cautious, they may smoke less, participate in stock markets less, and perhaps start own enterprises less, which may have a mixed impact on the recovery of the economy at a macro level. To complicate the matter even further, the subsequent generation who are born approximately one to two decades afterward – offspring of the war children – may show exactly the opposite behaviors. The policymakers in those countries and international organizations may consider different priorities for different generations, to facilitate the

recovery from devastating conflicts. Future studies may examine the trauma impact on other aspects related to profound individual preferences such as time preference and attitudes, and the impact of war trauma during the sensitive age on behavioral outcomes such as smoking and entrepreneurs.

Chapter 4

The Gendered Effects of Psychological Shock on Time Allocation: Evidence from the *Sewol* Ferry Disaster

Mental health issues are prevalent and costly. About 3.8% of the global population is suffering from depression as of 2019 (IHME 2023), and the negative consequences of poor mental health such as unemployment and earnings loss are well documented in the literature (Benham and Benham 1982; Biasi et al. 2021; Bubonya et al. 2017; Ettner et al. 1997; Hakulinen et al. 2019; Layard 2017; Lund et al. 2020; Mojtabai et al. 2015). On top of that, mental health issues appear to get worse over time. The sheer number of individuals suffering from depression increased from about 170 million in 1990 to about 280 million in 2019 (IHME 2023). However, how poor mental health leads to negative socio-economic outcomes is less investigated in the literature. We fill this gap by examining the effects of psychological shock on time allocation.

The *Sewol* ferry disaster provides a unique opportunity to examine how individuals adjust their time use upon an exogenous psychological shock. The *Sewol* ferry disaster occurred on April 16, 2014, near the southern coast of Korea. The disaster was unanticipated and rapid as the ferry completely sank in 52 hours after the first distress call. 304 passengers were lost out of 476 passengers and crews, and 86% of the victims were from a high school in *Ansan* city[1]. As one of the biggest maritime disasters in Korean history, the media was flooded with news on the severity of the disaster and the real-time rescue operations of the passengers. The failure of the res-

[1]Among the victims of the high school, 96% were high school students and 4% were teachers. There were 78 survivors from the school, 75 students and 3 teachers, but they lost their friends, teachers, and students.

cue operations and the following extensive media coverage were traumatic, especially to the individuals in and around *Ansan* city.

This paper estimates the causal effects of an exogenous psychological shock from the *Sewol* disaster on time allocation. The main data is from the 17th wave of the Korean Labor and Income Panel Study (KLIPS), a longitudinal and population-representative survey of South Korea. The *Sewol* ferry disaster occurred in the middle of the KLIPS survey period. The temporal and spatial variation of the disaster enables us to identify how the individuals adjusted their time use before and after the disaster for both the treatment group and the rest of South Korea. We investigate the distributional changes in time uses as the effects of the disaster may not be unidirectional. The heterogeneous effects of psychological shock and the evolution of the effects of the disaster are also explored. Lastly, we discuss the potential mechanisms.

We find that the disaster led males to substitute market work with housework and leisure on average. For females, the disaster increased market work and leisure without a TV but decreased housework, childcare, and leisure with a TV. For both genders, the distributions of market work had bidirectional shifts toward both zero and ten hours. The individuals seem to use market work and/or leisure as coping mechanisms to distract themselves from the disaster. In line with the hypothesis, the increase in market work was concentrated among the females with a school-age child in their households. The evolution of the effects for males shows a persistent decrease in market work and an increase in leisure throughout the sample period. For females, the increase in market work, and the decrease in housework and leisure with a TV persisted until the end of the sample period.

Intriguingly, the distributions of time uses for the individuals not residing in the treatment group remained surprisingly stable before and after the disaster. Thus, the results are stable between before-after estimates for the treatment group and

difference-in-differences estiamtes with the individuals outside of the treatment group as a control group. The treatment group specification as counties in and around *Ansan* city is further empirically justified by a donut analysis using distance from *Danwon* high school as another intensity of the disaster measure since 86% of the victims are from *Danwon* high school. The effects are concentrated in the counties within 15 km of *Danwon* high school, which is practically the same as the counties in and around *Ansan* city.

This paper makes three contributions to the growing literature on the economics of mental health. First, this study provides the first evidence on the causal effects of a psychological shock on time use. While the literature extensively examines the shocks affecting mental health[2], the causal effects of mental health on economic outcomes are less examined and mostly focused on labor market outcomes (Benham and Benham 1982; Biasi et al. 2021; Bubonya et al. 2017; Ettner et al. 1997; Hakulinen et al. 2019; Layard 2017; Lund et al. 2020; Mojtabai et al. 2015). A few exceptions include Jácome [2020], Angelucci and Bennett [2021], and Bhat et al. [2022] for examining the effects of mental health on criminal activity, preferences, and more.

Second, this paper complements the theoretical attempts to understand the effects of mental health on socio-economic outcomes (De Quidt and Haushofer 2016; Ridley et al. 2020). Not only an exogenous one-time psychological shock is the most parsimonious case and speaks directly to the existing economic theory of mental health (De Quidt and Haushofer 2016), but also time is one of the most primitive forms of resources to understand economic behaviors. The *Sewol* ferry disaster was

[2]A non-exhaustive list of the shocks include unemployment (Bandiera et al. 2017; Kuhn et al. 2009; Marcus 2013; Pierce and Schott 2020), income and wealth shocks (Apouey and Clark 2015; Banerjee et al. 2015; Cesarini et al. 2016; Christian et al. 2019; Friedman and Thomas 2009; Haushofer and Shapiro 2016; Haushofer and Shapiro 2018; Lindqvist et al. 2020; McInerney et al. 2013; Wolfe et al. 2012), disasters (Frankenberg et al. 2008; Thomas et al. 2021), social status (Clark 2003; Katz et al. 2001; Kling et al. 2007; Ludwig et al. 2012), and fear and worries (Avdic et al. 2021; Cornaglia et al. 2014; Dustmann and Fasani 2016; Kim and Kim 2018).

on one of the most vulnerable populations in mental health, South Korea[3]. Thus, the evidence provides an upper bound of the effects of mental health if the effects are monotonically increasing with the existing mental health issues.

Third, this study explores the immediate evolution of the effects of psychological shock on time use. Identifying the evolution of the effects is essential to optimize policy interventions. The stable effects of psychological shock for the working-age population throughout the sample period suggest that policy interventions toward the individuals around the center of shock may be effective. While the South Korean government organized *Ansan Mental Health Trauma* center 15 days after the disaster, the center mostly catered to targeted audiences such as victims and school-aged teenagers. The evidence suggests that it may be worthwhile to extend the target population to the residents of the affected areas.

The remainder of the paper is organized as the following. In Section 1, we describe the context and data. Section 2 presents the identification strategy and empirical results, and Section 3 explores the evolution of the effects. Section 4 provides a discussion of possible mechanisms. Finally, Section 5 concludes.

4.1 Sewol Ferry Disaster and Data

The *Sewol* ferry disaster unexpectedly occurred on April 16, 2014. The ferry departed from Incheon at 9 pm on April 15th to Jeju island following its regular schedule. While the ferry was supposed to arrive at Jeju island by 10 am on the 16th, the ferry started capsizing around 9 am on the 16th. The ferry completely sank after 52 hours although the first distress call was made 6 minutes after the ferry started capsizing.

[3]As of 2014, when the *Sewol* ferry disaster occurred, South Korea's suicide rate was 29.21 (per 100,000 population). In comparison, the suicide rate in the United States of America was only 14.12, and the global suicide rate was 10.17(IHME 2023).

As one of the most devastating disasters in Korean history, 304 individuals were lost out of 476 passengers and crew members. Among the casualties, 251 were high school students on their field trip from *Danwon* high school in *Ansan* city. The city was designated as a Special Disaster Zone 6 days after the ferry started capsizing. The media were flooded with the severity of the event, real-time information on the rescue operations, and who was responsible for the disaster over the next several months.

The *Sewol* disaster was particularly traumatic to the residents in and around *Ansan* city for two reasons. First, most of the victims of the disaster, *Danwon* high school students, were concentrated in and around the city. Accordingly, studies have reported that the individuals in the communities of the high school experienced severe stress and trauma (Yang et al. 2015; Han et al. 2017). Second, physical distance to the *Danwon* high school affects individuals' emotional responses to the disaster as they can better relate to the disaster with physical proximity (Williams and Bargh 2008; Trope and Liberman 2003; Trope and Liberman 2010). Therefore, we define the treatment group as the individuals residing in *Ansan* city, its neighboring counties, and the neighboring city where cremation was done (see figure 4.1). We empirically test the choice of the treatment group in the next section.

Our main dataset is the 17th wave of the Korean Labor Income Panel Study (KLIPS), a nationally representative longitudinal survey of South Korea. The 17th wave of the KLIPS contains rich socioeconomic and demographic information with two unique features. First, over 93 percent of the survey was conducted from March to June 2014, and the *Sewol* disaster unexpectedly occurred on April 16, in the middle of the survey. Second, the KLIPS added a special section for time use only for 2014, the 17th wave. Therefore, we can compare how individuals used their time before and after the disaster. We include non-proxy-interviewed individuals of age 20 to 60 with the time use reference date the day before the interview to reduce confounding

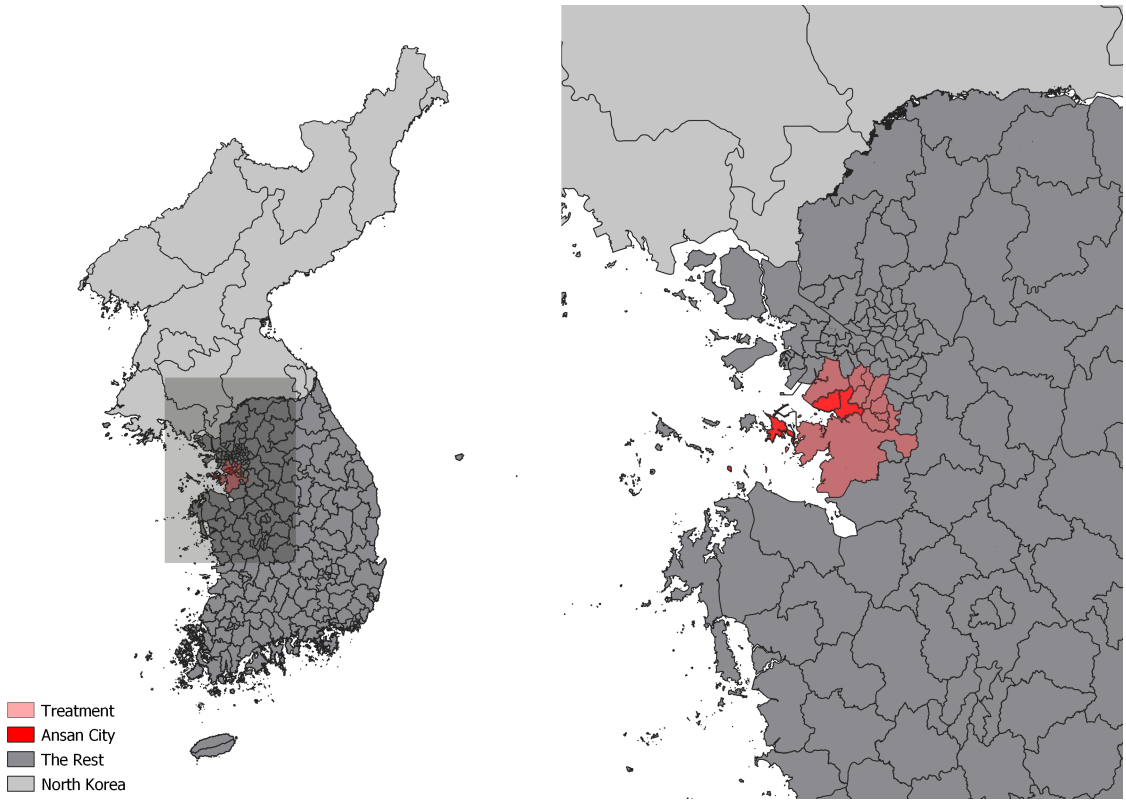

Figure 4.1: Map of *Ansan* city and the treatment group

Note: The left panel shows the map of the Korean peninsula, and the right panel shows *Ansan* city and the treatment group. The Korean peninsula is categorized into *Ansan* city, the treatment group (including *Ansan* city), the rest of South Korea, and North Korea. *Ansan* city and counties around *Ansan* city and Suwon county are categorized as the treatment group with their geographic closeness to *Ansan* city.

effects from schooling, retirement, and recall errors. We exclude those surveyed on the day of the disaster as the treatment assignment is based on the survey date. Our final sample includes 6,868 individuals.

Figure 4.2 plots the sample distributions of survey dates for the treatment group and the rest of the sample by gender in panels A and B. The sample distributions for the treatment group are distinctly different from the ones for the rest of the sample. For the treatment group, the dip around 30 days and the peak around 55 days after the disaster suggest that some individuals may have postponed their survey

participation[4]. While the timing of survey participation is concerning, the difference in the attrition rates is only 0.1 percent point between the treatment group and the rest of the sample.

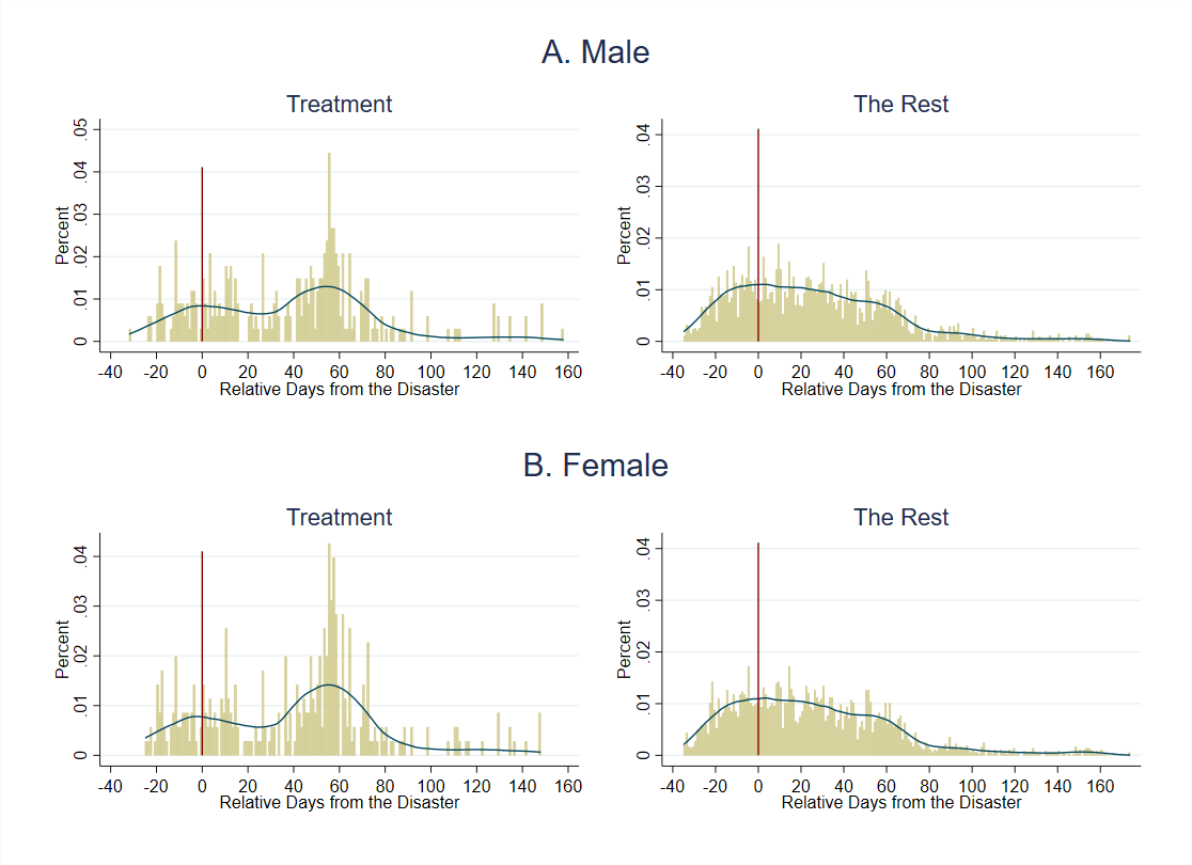

Figure 4.2: Distributions of observations by relative days from the disaster

Note: The left panels show the distributions of the number of observations for the treatment group while the right panels show the distributions for the rest of South Korea. The x-axis is the relative days from the disaster, where day 0 represents the day of the disaster. The y-axis is the percent of observations surveyed per day.

In the 17th wave of KLIPS, the respondents were asked to choose a primary activity among 16 time use categories for every 30-minute interval for a reference date.

[4]figure A5 shows the distributions of survey dates for the previous year's KLIPS 2013. The smoother distribution of KLIPS 2013 suggests that there was a selection in the survey timing in KLIPS 2014. The selection may introduce bias to our estimates if the selection is non-random in terms of time use. We indirectly test the selection issue by examining how the treatment effects evolve over time below in figures 5 and 6.

Table 4.1 shows the 16 time use categories and the proportion of zero values. Several categories have significant proportions of zero values. For instance, over 90 percent of the sample reports zero values for the side job, job search, meeting a coworker, religion, self-development, volunteering, and meeting family time. Therefore, we group similar time uses into higher categories and use the original time use variable only if it does not have too many zero values. All labor market-related times are grouped as market work. Personal care and sleeping time are grouped as personal time. The original housework and childcare are used on their own as they do not suffer from too many zero values issue. Leisure is originally surveyed as one variable, but we split it into one involving a TV and the other without a TV as TV was a major channel through which traumatic disaster-related news was disseminated (Bu et al. 2021; Holman et al. 2014).

Table 4.2 shows the summary statistics of the dependent variables by gender. Columns (1) and (2) report the mean and standard deviation of the entire sample, and we stratify our sample in columns (3) – (6) by two indicator variables: whether the individual was surveyed before or after the disaster and whether the individual was in the treatment group. While column (7) reports the difference before and after the disaster for the treatment group, column (8) shows the difference in differences between columns (3) – (6). We analyze male and female samples in panels A and B separately as the different nature of time uses by gender would result in heterogeneous effects of the disaster. For example, the average male and female spend 0.3 and 2.58 hours a day on housework, respectively.

Column (7) of panel A for the male sample indicates that the disaster led to significant decreases in market work and personal time with significant increases in housework, childcare, and leisure without a TV. In column (7) of panel B for the female sample, we can only find a significant decrease in leisure with a TV and a sig-

Table 4.1: Time Use Variables

Variable	Activities (1)	Percent Zero (2)
Panel A. Market Work		
Main Job	Main employment activities (worker's main work-related activities in general)	41.29
Side Job	Side employment activities (additional income activities other than the main work)	99.74
Job Search	Job search (resume writing, employment agency visit, interview etc.)	99.10
Commute	Commute time	40.96
Meeting Coworker	Phone calls and meetings with colleagues	96.35
Panel B. Housework		
Housework	Household activities (meal preparation, laundry, cleaning, grocery shopping etc.)	45.73
Panel C. Childcare		
Childcare	Childcare (bathing, sleeping, playing, dropping off, studying)	81.03
Panel D. Personal		
Personal care	Personal care (meals, personal hygiene, preparation for going out, etc.)	1.35
Sleep	Sleeping time	0.07
Panel E. Leisure w/ TV		
Leisure w/ TV	Leisure activities (TV/video/internet, movies etc.)	12.45
Panel F. Leisure w/o TV		
Leisure w/o TV	Leisure activities (newspapers/magazines, movies/exhibitions/sports, exercise etc.)	24.30
Panel G. Other		
Religion	Religious activities (personal religious activities, religious gatherings etc.)	96.36
Self-development	Academic and self-development activities	91.10
Volunteer	Volunteer (daily feed, traffic guide, volunteering, reserve forces duty etc.)	99.40
Family Care	Non-child family care (including patient care and excluding meal preparation)	97.10
Meeting Friends	Personal phone calls and gatherings with friends	86.36
Meeting Family	Phone calls and gatherings with family and relatives	93.91

Note: This table shows the definition of the original time use variables in the paper. The 17th wave of KLIPS asked individuals to select activities from the 17 options with 30-minute intervals for a reference date. Each panel shows the higher category of time use variables to be used in the analyses. Column (1) shows the activities considered in each of time use categories, and column (2) shows the proportion of zero hours reported in the sample.

Table 4.2: Time Use Variables Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	Entire Sample		Yes	Yes	No	No	Diff:	DID
Post	Mean	Std. Dev.	Yes	No	Yes	No	(3)-(4)	
Panel A. Male								
Market work	7.64	5.13	7.55	8.92	7.71	7.41	-1.38*	-1.67**
Housework	0.30	0.80	0.31	0.12	0.31	0.28	0.19**	0.16*
Childcare	0.23	0.85	0.23	0.07	0.25	0.20	0.16**	0.12
Personal	9.91	1.69	9.82	10.32	9.86	10.03	-0.51**	-0.34
Leisure w/ TV	1.83	1.53	1.92	1.89	1.73	2.04	0.03	0.33
Leisure w/o TV	2.42	2.64	2.66	1.43	2.47	2.30	1.24***	1.07***
Sample Size	3,255		252	52	2,144	807		
Panel B. Female								
Market work	4.57	5.00	4.02	3.27	4.69	4.47	0.76	0.54
Housework	2.58	2.17	2.49	3.06	2.58	2.58	-0.57	-0.58
Childcare	0.79	2.07	0.87	0.72	0.72	0.94	0.15	0.36
Personal	9.88	1.67	10.07	10.15	9.83	9.92	-0.07	0.02
Leisure w/ TV	2.01	1.51	2.06	2.74	1.95	2.14	-0.68***	-0.48*
Leisure w/o TV	2.36	2.50	2.82	1.90	2.38	2.21	0.91***	0.75**
Sample Size	3,613		271	54	2,343	945		

Note: This table reports the sample means and standard deviations of time use variables in columns (1) and (2). Columns (3)-(6) report the sample averages stratified by the treatment group indicator ($Treatment$) and post-disaster indicator ($Post$). The individuals in the counties in and around *Ansan* city are taken as a treatment group as most of the victims are from *Danwon* high school located in *Ansan* city. Column (7) shows the pre-post difference within the treatment group between columns (3) and (4), and column (8) shows the difference-in-differences between columns (3)-(6). *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

nificant increase in leisure without a TV. Interestingly, we find similar results between columns (7) and (8). Of course, the disaster would have affected the individuals outside of the treatment group, but the order of magnitude would be much bigger for the treatment group than for the rest of the country. Overall, if we assign the individuals outside of the treatment group as a control group, we seem to get underestimates of the true effects in column (7) as if we had a contaminated control.

Table 4.3 reports covariates with the same structure as in table 4.2. Column (7) tests the balancedness of the treatment group before and after the disaster. We can find a few significant unbalancedness in educational attainments for both genders and marital status for males. However, the unbalancedness seems to be related to the timing of survey participation by demographic characteristics. The indicators for

higher socioeconomic status such as family income and educational attainment are associated with later survey participation even with the county fixed effects, possibly because of the differences in their value of time (Hamermesh and Lee 2007). As such, we no longer find any significance in the difference in differences in column (8). However, we should be cautious in interpreting before and after estimates as there may be non-random sample selection for the treatment group alone. Our average samples are a 40-year-old married male and a 41-year-old married female with high school degrees.

4.2 Effects of *Sewol* ferry disaster

4.2.1 Baseline Estimation

To examine how the *Sewol* disaster affected the allocation of time, we employ a before and after model with the treatment group:

$$Y_i = \beta Post_i + X_i\Gamma + \delta_{county} + \epsilon_i \qquad [1]$$

where Y_i represents the unconditional and extensive margins of time use in hours, $Post_i$ is an indicator for being surveyed after the disaster. X_i includes demographic and socioeconomic covariates, and δ_{county} is the county fixed effect. The coefficient of interest is β as it captures the reduced-form effects of the disaster. The treatment group sample is stratified by gender for the analysis as the nature of time use is noticeably different by gender (see table 4.2). We use ordinary least squares, and the standard errors are clustered at the county level. Note that our estimates should be considered as an intent-to-treat since some people may have not heard about the disaster by their interview dates, although it was very unlikely due to the heavy

Table 4.3: Balancedness Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	Entire Sample		Yes	Yes	No	No	Diff:	DID
Post	Mean	Std. Dev.	Yes	No	Yes	No	(3)-(4)	
Panel A. Male								
Age	40.35	11.33	40.50	38.83	40.38	40.34	1.68	1.65
Mandatory education	0.97	0.17	0.99	0.97	0.97	0.96	0.02	0.00
High school education	0.91	0.29	0.96	0.79	0.92	0.87	0.17*	0.12
Tertiary education	0.34	0.48	0.48	0.27	0.35	0.29	0.21**	0.15
Subjective good health	0.67	0.47	0.77	0.77	0.68	0.60	0.00	-0.07
Married	0.60	0.49	0.67	0.48	0.61	0.56	0.19*	0.14
Number of family members	2.40	1.05	2.41	2.23	2.47	2.24	0.18	-0.05
Household income (in millions KRW)	9.16	1.00	9.31	8.96	9.25	8.88	0.36	-0.02
Having any school-age child	0.31	0.46	0.36	0.28	0.31	0.28	0.08	0.04
Sample Size	3,255		252	52	2,144	807		
Panel B. Female								
Age	41.25	11.21	40.22	41.17	41.08	42.05	-0.95	0.01
Mandatory education	0.95	0.22	0.98	0.93	0.95	0.92	0.05	0.02
High school education	0.87	0.34	0.94	0.85	0.88	0.81	0.09*	0.02
Tertiary education	0.27	0.45	0.31	0.27	0.29	0.22	0.04	-0.02
Subjective good health	0.62	0.49	0.78	0.68	0.62	0.57	0.10	0.04
Married	0.70	0.46	0.75	0.65	0.70	0.70	0.10	0.10
Number of family members	2.47	1.01	2.53	2.48	2.52	2.35	0.04	-0.12
Household income (in millions KRW)	9.25	0.91	9.43	9.20	9.32	9.03	0.23	-0.06
Having any school-age child	0.35	0.48	0.44	0.34	0.34	0.35	0.10	0.11
Sample Size	3,613		271	54	2,343	945		

Note: This table reports the sample means and standard deviations of covariates in columns (1) and (2). Columns (3)-(6) report the sample averages stratified by the treatment group indicator (*Treatment*) and post-disaster indicator (*Post*). The individuals in the counties in and around *Ansan* city are taken as a treatment group as most of the victims are from *Danwon* high school located in *Ansan* city. Column (7) shows the pre-post difference within the treatment group between columns (3) and (4), and column (8) shows the difference-in-differences between columns (3)-(6). *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

media coverage.

Table 4.4 reports the β estimates of equation [1] for unconditional time use. In panel A, the disaster reduced market work and increased housework and leisure with or without a TV for males. For females, market work and leisure without a TV were increased while housework, childcare, and leisure with TV were decreased (see panel B). We can find multiple-hypothesis adjusted p-values in the squared brackets below standard errors, and the significance of the effects survives even after the Hochberg multiple hypothesis adjustments. The magnitudes of the effects are large. Based on the pre-disaster mean, housework increased by 223 percent and market work decreased by 27 percent for males. Such a high percentage increase in housework can be attributed to the small baseline mean value. For females, market work increased by 59 percent and childcare decreased by 73 percent. As the expected utility from engaging in the type of time use would have changed with the disaster, males mainly re-allocated market work into leisure, and females did housework and childcare into market work. The individuals in the treatment group seem to cope with the trauma from the disaster by increasing leisure or market work (Holman et al. 2014; Kleiber et al. 2002). Females would have decreased leisure with a TV by rational ignorance as individuals were naturally exposed to disaster-related news with a TV (Holman et al. 2014).

Table 4.5 presents the β estimates of equation [1] for the extensive margin of time use. Personal time is not included as a dependent variable as there was no variation in its extensive margin. In panel A, males decreased market work and increased housework and leisure with a TV after the disaster. The significant effects on market work and housework account for 23 and 128 percent of the pre-disaster mean. Such large magnitudes of the decreases in the extensive margin of market work are striking. While we do not find any significant effects of the disaster on time use for females in

Table 4.4: Estimated Change of Unconditional Time Use after the *Sewol* Ferry Disaster

	Market work (1)	Housework (2)	Childcare (3)	Personal (4)	Leisure w/ TV (5)	Leisure w/o TV (6)
Panel A. Male						
Post	-2.439***	0.259**	0.064	-0.253	0.448**	1.039***
	(0.579)	(0.089)	(0.109)	(0.182)	(0.181)	(0.315)
Hochberg adjusted p-value	[0.005]	[0.056]	[0.569]	[0.384]	[0.093]	[0.035]
Sample mean (hours)	8.92	0.12	0.07	10.32	1.89	1.43
"Magnitude of β estimated in Panel A as % relative to the sample mean"	-27.3	223.3	90.8	-2.5	23.7	72.8
Sample Size	304	304	304	304	304	304
Panel B. Female						
Post	1.934**	-1.032**	-0.525**	-0.028	-0.502**	0.751***
	(0.818)	(0.376)	(0.189)	(0.346)	(0.195)	(0.166)
Hochberg adjusted p-value	[0.076]	[0.076]	[0.076]	[0.936]	[0.076]	[0.006]
Sample mean (hours)	3.27	3.06	0.72	10.15	2.74	1.90
"Magnitude of β estimated in Panel B as % relative to the sample mean"	59.2	-33.7	-72.6	-0.3	-18.3	39.5
Sample Size	325	325	325	325	325	325

Note: This table shows the before-after estimates for the treatment group from equation [1]. Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

panel B, 31 percent increase in market work and 21 percent increase in childcare are noticeably large.

4.2.2 Timing of Time Re-allocations

When do individuals reallocate their time? To examine the timing of the time re-allocation, we divide a day into the morning (6:00-12:00), daytime (12:00-19:00), evening (19:00-22:00), and night (22:00-6:00). Leisure was not surveyed separately with and without a TV at each time of the day, so leisure as a whole is taken as a dependent variable. Table 4.6 reports the β estimates of equation [1] at each time of the day. Males decreased market work throughout the day. The time for market work was significantly reallocated to leisure during morning and evening and to housework during daytime and evening. On the other hand, females substituted housework and childcare with market work throughout the day except in the evening.

4.2.3 Distributional Changes

The effects of the disaster on time use may not be unidirectional depending on the nature of the time use category. To test this hypothesis, we examine how the distributions of time use changed before and after the disaster. Figure 4.3 shows the distributional changes for males, respectively for the treatment and the rest of the sample. The blue lines are for the distributions of time uses before the disaster, and the red ones are for the distributions after the disaster. While the distributions for the rest of the sample were surprisingly stable before and after the disaster, those for the treatment group changed dramatically. For the treatment group, the distribution of market work got more bimodal after the disaster with higher concentrations around three and ten hours. An explanation for such a pattern would be that in-

Table 4.5: Estimated Change of Extensive Margin of Time Use after the *Sewol* Ferry Disaster

	Market work (1)	Housework (2)	Childcare (3)	Leisure w/ TV (4)	Leisure w/o TV (5)
Panel A. Male					
Post	-0.212**	0.138***	0.019	0.079*	0.099
	(0.071)	(0.035)	(0.042)	(0.044)	(0.107)
Hochberg adjusted p-value	[0.048]	[0.010]	[0.667]	[0.297]	[0.667]
Sample mean	0.92	0.11	0.04	0.90	0.66
"Magnitude of β estimated in Panel A as % relative to the sample mean"	-23.0	128.3	47.5	8.7	15.0
Sample Size	304	304	304	304	304
Panel B. Female					
Post	0.137	0.018	0.024	0.011	0.055
	(0.089)	(0.036)	(0.049)	(0.021)	(0.065)
Hochberg adjusted p-value	[0.637]	[0.637]	[0.637]	[0.637]	[0.637]
Sample mean	0.44	0.78	0.11	0.97	0.84
"Magnitude of β estimated in Panel B as % relative to the sample mean"	31.1	2.3	21.4	1.1	6.6
Sample Size	325	325	325	325	325

Note: This table shows the before-after estimates for the treatment group from equation [1]. Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table 4.6: Estimated Change in Time Allocation by Daily Clock Time

	Market work (1)	Housework (2)	Childcare (3)	Leisure w/ TV (4)	Leisure w/o TV (5)
Male					
Panel A. Morning					
Post	-0.706*	0.042	-0.007	-0.136	0.576***
	(0.335)	(0.080)	(0.024)	(0.329)	(0.169)
Panel B. Daytime					
Post	-0.930***	0.129*	0.065	0.051	0.177
	(0.253)	(0.061)	(0.087)	(0.156)	(0.233)
Panel C. Evening					
Post	-0.570*	0.090**	0.014	0.119	0.387*
	(0.264)	(0.039)	(0.055)	(0.078)	(0.186)
Panel D. Night					
Post	-0.234	-0.002	-0.007	-0.287	0.346
	(0.500)	(0.004)	(0.013)	(0.391)	(0.245)
Sample Size	304	304	304	304	304
Female					
Panel E. Morning					
Post	0.691*	-0.632	-0.136	0.174	0.082
	(0.359)	(0.357)	(0.080)	(0.138)	(0.179)
Panel F. Daytime					
Post	0.928**	-0.443**	-0.383***	0.041	0.266
	(0.395)	(0.178)	(0.120)	(0.160)	(0.226)
Panel G. Evening					
Post	0.109	0.102	0.010	0.008	-0.113
	(0.075)	(0.089)	(0.059)	(0.065)	(0.092)
Panel H. Night					
Post	0.206*	-0.060*	-0.015	-0.251	0.015
	(0.099)	(0.028)	(0.049)	(0.266)	(0.147)
Sample Size	325	325	325	325	325

Note: This table shows the before-after estimates for the treatment group from equation [1] for the morning (6:00-12:00), daytime (12:00-19:00), evening (19:00-22:00), and night (22:00-6:00). Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

dividuals may have coped with the disaster by distracting themselves by increasing either leisure or market work. We find clear decreases in personal, leisure with a TV and increases in housework, childcare, and leisure without a TV. The increase in leisure with a TV in table 4.2 seems to be driven by a long right tail, the outliers.

Figure 4.4 reports the distributional changes for females. We find a similar bi-modal change in market work as for males, but the shift towards ten hours is greater for females than for males. The disaster significantly decreased housework, childcare,

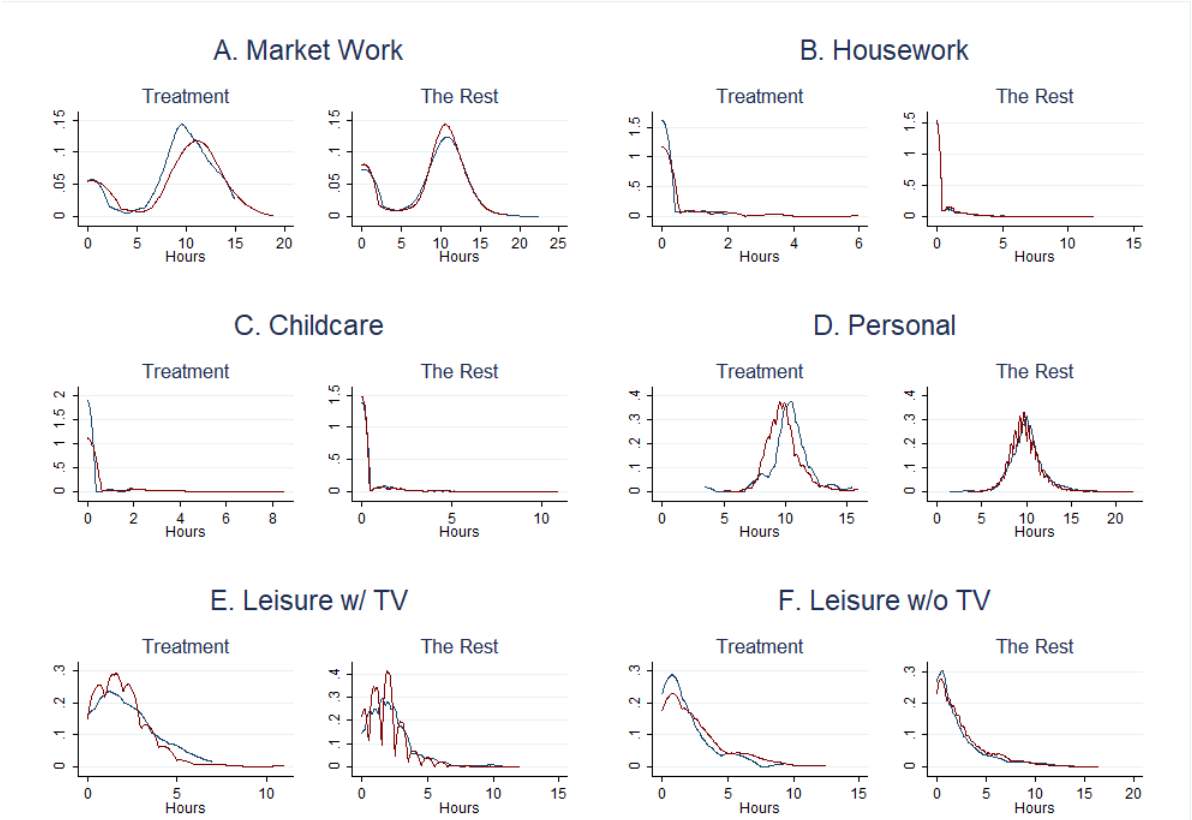

Figure 4.3: Distribution of time use before and after *Sewol* disaster for males

Note: This figure shows the time use distributions of the treatment group and the rest of South Korea for the male sample. The blue lines are kernel densities of the pre-disaster sample and the red ones are for the post-disaster sample. The x-axis is the number of hours spent on the time use category.

and leisure with a TV with a sizable increase in leisure without a TV. The decrease in leisure with a TV and an increase in leisure without a TV could be explained by rational ignorance. As almost all media repeatedly reported updates about the disaster, rescue, and its repercussion on society in real time, the individuals in the treatment group may have tried to stay away from further traumatization by reducing time spent on watching TV.

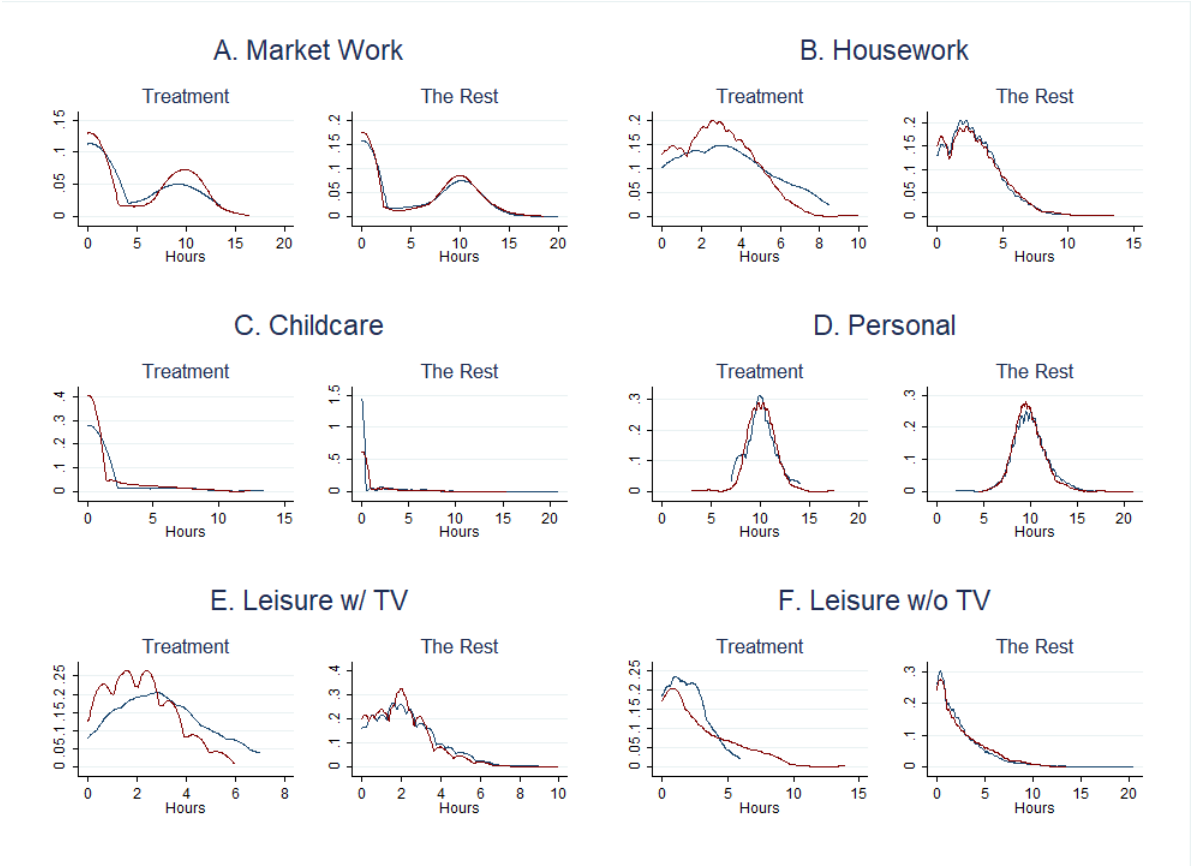

Figure 4.4: Distribution of detailed time use before and after *Sewol* disaster for females

Note: This figure shows the time use distributions of the treatment group and the rest of South Korea for the female sample. The blue lines are kernel densities of the pre-disaster sample and the red ones are for the post-disaster sample. The x-axis is the number of hours spent on the time use category.

4.2.4 Robustness Checks

The exchangeability of the treatment group before and after the disaster is the key assumption for the validity of the β estimates of the equation [1]. While a few significant differences in covariates in table 4.3 was concerning, the difference in differences in table 4.3 and distributional analyses in figures 4.3 and 4.4 suggest that the individuals outside of the treatment group may serve as a valid control group. In the worst-case scenario, the treatment effects would be biased toward zero if the

control group is contaminated and the effects for the control group are in the same direction as those of the treatment group.

We conduct a robustness check by employing the following difference-in-differences model:

$$Y_i = \beta_1 Post_i + \beta_2 Post_i \times Treatment_i + X_i\Gamma + \delta_{county} + \epsilon_i \qquad [2]$$

where Y_i represents unconditional time use in hours, $Post_i$ is an indicator variable for the individuals surveyed after the disaster. $Treatment_i$ is an indicator variable for the treatment group, and $Post_i \times Treatment_i$ is the interaction term between $Post_i$ and $Treatment_i$. X_i is demographic and socioeconomic covariates, and δ_{county} indicates the county fixed effect as in equation [1]. The coefficient estimate of β_2 captures the effects of the disaster on the treatment group compared to the rest of the sample. We use ordinary least squares, and the standard errors are clustered at the county level.

The estimates of equation [2] are reported in table 4.7 for males and females, respectively. Intriguingly, the difference in differences estimates in table 4.7 are not statistically different from the before and after estimates in table 4.4. The individuals outside of the treatment group seem to serve as a reasonable control group as their stable distributions of time use suggest in figures 3 and 4. Having a control group is important for controlling seasonality and time trend in time use.

Another key assumption is the choice of treatment group. The original definition of the treatment group is the individuals residing in *Ansan* city, its neighboring counties, and the neighboring city where cremation was done. The choice of treatment

Table 4.7: Difference-in-Differences

	Market work (1)	Housework (2)	Childcare (3)	Personal (4)	Leisure w/ TV (5)	Leisure w/o TV (6)
Panel A. Male						
Post	0.277	0.050	0.021	-0.130	-0.301***	0.182
	(0.251)	(0.033)	(0.033)	(0.100)	(0.085)	(0.166)
Post × Treatment	-2.511***	0.213***	0.022	-0.313	0.527*	0.909**
	(0.511)	(0.062)	(0.153)	(0.212)	(0.270)	(0.386)
Panel B. Female						
Post	-0.006	0.238**	-0.172**	-0.196*	-0.100	0.210
	(0.281)	(0.094)	(0.077)	(0.101)	(0.071)	(0.146)
Post × Treatment	2.009***	-1.162***	-0.169	0.097	-0.456***	0.306
	(0.701)	(0.336)	(0.166)	(0.357)	(0.161)	(0.281)
Sample Size	3,228	3,228	3,228	3,228	3,228	3,228

Note: This table shows the estimates from equations [2] and [3] for males. Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

group is tested with the following donut analysis:

$$
\begin{aligned}
Y_i = \gamma_1 Post_i &+ \gamma_2 Post_i \times 1[Distance \leqslant 15km]_i \\
&+ \gamma_3 Post_i \times 1[15km < Distance \leqslant 25km]_i \\
&+ \gamma_4 Post_i \times 1[25km < Distance \leqslant 35km]_i \\
&+ X_i\Gamma + \delta_{county} + \epsilon_i \qquad [3]
\end{aligned}
$$

where we take equation [2] and replace $Post_i \times Treatment_i$ with the interaction terms between $Post_i$ and the donut indicators for the counties within 15km, 15-25km, and 25-35km radius from the *Danwon* high school. The 15 km radius approximately covers the original choice of the treatment group.

Table 4.8 shows the estimates of equation [3] for males and females, respectively. An alternative treatment group of individuals within the 15 km radius of *Danwon* high school exhibit significant effects of the disaster, and the effects completely disappear after the 25 km radius. The magnitudes of the effects are very similar to the before and after estimates in table 4.4 and difference-in-differences estimates in table 4.8. The individuals between 15 km and 25 km only changed their housework time for males and childcare for females with no other time use adjustments after the disaster. The distance analyses in table 4.8 show weak evidence for spatial spillover effects.

Table 4.8: Alternative Treatment Group with Distance from *Danwon* high school

	Market work (1)	Housework (2)	Childcare (3)	Personal (4)	Leisure w/ TV (5)	Leisure w/o TV (6)
Panel A. Male						
Post	0.196	0.081**	0.026	-0.150	-0.329***	0.158
	(0.302)	(0.039)	(0.041)	(0.120)	(0.107)	(0.205)
Post × 1[Distance ⩽ 15km]	-2.286***	0.179***	0.025	-0.388**	0.499*	0.835**
	(0.532)	(0.067)	(0.158)	(0.191)	(0.269)	(0.417)
Post × 1[15km ⩽ Distance ⩽ 25km]	-0.136	-0.156**	-0.005	0.276	0.056	0.359
	(0.802)	(0.077)	(0.088)	(0.290)	(0.213)	(0.379)
Post × 1[25km ⩽ Distance ⩽ 35km]	0.705	-0.052	-0.034	-0.131	0.188	-0.182
	(0.560)	(0.078)	(0.080)	(0.210)	(0.190)	(0.482)
Panel B. Female						
Post	-0.410	0.214*	-0.046	-0.099	-0.093	0.207
	(0.256)	(0.119)	(0.076)	(0.115)	(0.088)	(0.139)
Post × 1[Distance ⩽ 15km]	2.454***	-1.160***	-0.296*	0.003	-0.468***	0.300
	(0.697)	(0.344)	(0.169)	(0.365)	(0.172)	(0.280)
Post × 1[15km ⩽ Distance ⩽ 25km]	1.765	0.104	-0.493*	-0.351	-0.125	0.172
	(1.284)	(0.281)	(0.283)	(0.330)	(0.180)	(0.512)
Post × 1[25km ⩽ Distance ⩽ 35km]	0.904	0.063	-0.345	-0.289	0.078	-0.141
	(0.773)	(0.227)	(0.211)	(0.301)	(0.172)	(0.493)
Sample Size	3,594	3,594	3,594	3,594	3,594	3,594

Note: This table shows the estimates from equations [2] and [3] for females. Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

4.2.5 Heterogeneity

To gain insight into the heterogeneous effects of the disaster, we use triple differences with individual characteristics:

$$\begin{aligned} Y_i = {} & \theta_1 Post_i + \theta_2 Group_i + \theta_3 Post_i \times Group_i + \theta_4 Treatment_i \times Group_i \\ & + \theta_5 Post_i \times Treatment_i + \theta_6 Post_i \times Treatment_i \times Group_i \\ & + X_i \Gamma + \delta_{county} + \epsilon_i \qquad [4] \end{aligned}$$

where $Group_i$ is an indicator variable for the group of interest. The coefficient of interest is θ_6 as it represents the group-specific effects of the disaster compared to the baseline effects on the treatment group. There are two main groups of interest. First, we examine the effects with whether the household has a school-aged child as they would be able to better relate to the disaster victims with the victims being mostly high school students. Second, we consider whether the individual is in a family business, that is, either being self-employed or working for no pay for a family business. The individuals in a family business would have fewer constraints in their time use relative to employees, so we would better observe the relative changes in the expected utility of each time use category.

Table 4.9 reports the θ_5 and θ_6 estimates of the equation [4] for unconditional time use. Interestingly, males adjust their time use with neither school-age child nor family business (see panels A and B). Males marginally increased childcare by 22 minutes with a school-age child, if anything. However, with a school-age child in panel C, females decreased housework even further and reallocated the time to market work and childcare. The females in a family business did not increase their market work and used the time on personal time and leisure with a TV. However, the increase in

leisure with a TV is driven by outliers as we have seen in the distributional analysis in figures 4.3 and 4.4. The increase in personal time is concentrated in personal care, not in sleeping time.

Table 4.10 presents the θ_5 and θ_6 estimates of the equation [4] for the extensive margin of time use. We can see that males with a school-age child in their household further stopped having any leisure with a TV (see panel 1), which would reflect rational ignorance. TV incessantly broadcasted disaster-related news for the next several months after the disaster. While TV was informative about the progress of the disaster and the rescue operations when there was a hope of rescue, the news soon became unproductive and got politicized about whom to blame. For females, we can find a significant decrease in housework and an increase in leisure with a TV. While it is surprising to find an increase in leisure with a TV, the increase is concentrated in the early days when the news was relatively informative and constructive.

4.3 Evolution of the Treatment Effects

A natural following question is how long the effects of the disaster last. Although the time use section was added to neither earlier nor later waves of the KLIPS, we can examine how the effects of the shock evolve over the sample period. Loosely speaking, we can estimate the impulse-response function of the effects of the disaster on the treatment group by estimating the equation [2] with a moving post-disaster subsample. Specifically, we include a 30-day moving sample after the disaster up to day 65 with all the pre-disaster sample. With pre-disaster sample always included, we get our first estimate including post-disaster day 1-30 sample, the second estimate including the day 2-31 sample, and repeat the estimation until we get the last one including the day 36-65 sample. However, we should be cautious in interpreting the

Table 4.9: Triple Interaction Heterogeneity Analyses - Unconditional

	Market work (1)	Housework (2)	Childcare (3)	Personal (4)	Leisure w/ TV (5)	Leisure w/o TV (6)
Panel A. School-age Child (Male)						
Post × Treatment	-2.410***	0.250***	-0.077	-0.410	0.608	0.865**
	(0.519)	(0.057)	(0.152)	(0.314)	(0.391)	(0.373)
Post × Treatment × School-age Child	-0.334	-0.143	0.362*	0.322	-0.219	0.119
	(2.027)	(0.210)	(0.197)	(0.533)	(0.518)	(0.539)
Panel B. In Family Business (Male)						
Post × Treatment	-2.324***	0.239***	0.003	-0.518	0.587	0.897**
	(0.604)	(0.077)	(0.170)	(0.318)	(0.407)	(0.415)
Post × Treatment × Family Business	-1.554	-0.078	0.137	0.841	0.098	0.399
	(2.255)	(0.257)	(0.105)	(0.723)	(0.732)	(0.474)
Panel C. School-age Child (Female)						
Post × Treatment	1.244	-0.702*	-0.531**	-0.106	-0.409***	0.481*
	(0.755)	(0.362)	(0.248)	(0.471)	(0.136)	(0.288)
Post × Treatment × School-age Child	2.473***	-1.496**	1.027**	0.633	-0.088	-0.491
	(0.896)	(0.706)	(0.505)	(0.428)	(0.423)	(0.446)
Panel D. In Family Business (Female)						
Post × Treatment	2.443**	-0.944***	-0.203	-0.102	-0.703***	0.220
	(0.972)	(0.263)	(0.173)	(0.364)	(0.187)	(0.372)
Post × Treatment × Family Business	-3.387*	-0.813	0.199	1.261***	1.568***	0.667
	(2.043)	(1.201)	(0.259)	(0.337)	(0.323)	(0.738)

Note: This table shows the estimates from equation [4]. Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table 4.10: Triple Interaction Heterogeneity Analyses - Extensive Margin

	Market work (1)	Housework (2)	Childcare (3)	Leisure w/ TV (4)	Leisure w/o TV (5)
Panel A. School-age Child (Male)					
Post × Treatment	-0.174***	0.137***	0.016	0.158**	0.168
	(0.058)	(0.036)	(0.064)	(0.062)	(0.103)
Post × Treatment × School-age Child	-0.082	-0.088	0.049	-0.164**	-0.013
	(0.096)	(0.135)	(0.073)	(0.070)	(0.123)
Panel B. In Family Business (Male)					
Post × Treatment	-0.201***	0.135***	0.024	0.115*	0.123
	(0.057)	(0.047)	(0.070)	(0.064)	(0.137)
Post × Treatment × Family Business	-0.039	-0.103	0.025	0.035	0.207
	(0.074)	(0.208)	(0.055)	(0.147)	(0.125)
Panel C. School-age Child (Female)					
Post × Treatment	0.107	0.052	0.060	-0.005	0.065
	(0.105)	(0.049)	(0.044)	(0.032)	(0.075)
Post × Treatment × School-age Child	0.212	-0.121**	0.066	0.085*	-0.070
	(0.162)	(0.054)	(0.107)	(0.046)	(0.085)
Panel D. In Family Business (Female)					
Post × Treatment	0.212*	0.027	0.088	0.044*	0.047
	(0.119)	(0.049)	(0.058)	(0.024)	(0.097)
Post × Treatment × Family Business	-0.332	-0.024	-0.003	-0.091	-0.038
	(0.207)	(0.052)	(0.066)	(0.087)	(0.253)

Note: This table shows the estimates from equation [4]. Standard errors in parentheses are clustered on the county. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

results as there could be a selection in the timing of response, which is suggested in the distributions of observations in figure 4.2.

Figure 4.5 plots the coefficient estimates of β_2 for males against the relative days from the disaster with a 95% confidence interval. The evolution for market work exhibits a negative treatment effect from the very start, but the effect gets significant and greater in magnitude after 50 days after the disaster. The evolution may be explained by the fact that employees need some time to adjust working hours or quit their jobs. While housework, childcare, and personal time are not significantly changed over the entire sample period, we can see that the evolutions for leisure with and without a TV show increases. Especially the effects of the disaster on leisure without a TV get stronger and more significant over time. The pattern that the evolution of leisure with a TV loses its significance over time may be because the effects are coming from a few outliers. This is not surprising as most people got tired of news about the disaster as the news got politicized over time.

Female time use evolutions are examined in figure 4.6. We find a clear increase in market work. The increase gets significant around 37 days after the disaster, which may reflect the time required for finding a new job. Rational ignorance would explain the decrease in leisure with a TV as TV constantly broadcasted traumatic disaster-related news. Interestingly, the time in housework and leisure with a TV got reallocated to market work. The reallocation suggests that the expected utility of spending time on market work got higher than on housework and leisure without a TV. Females seem to prefer to cope with the disaster by engaging in market work than in leisure without a TV.

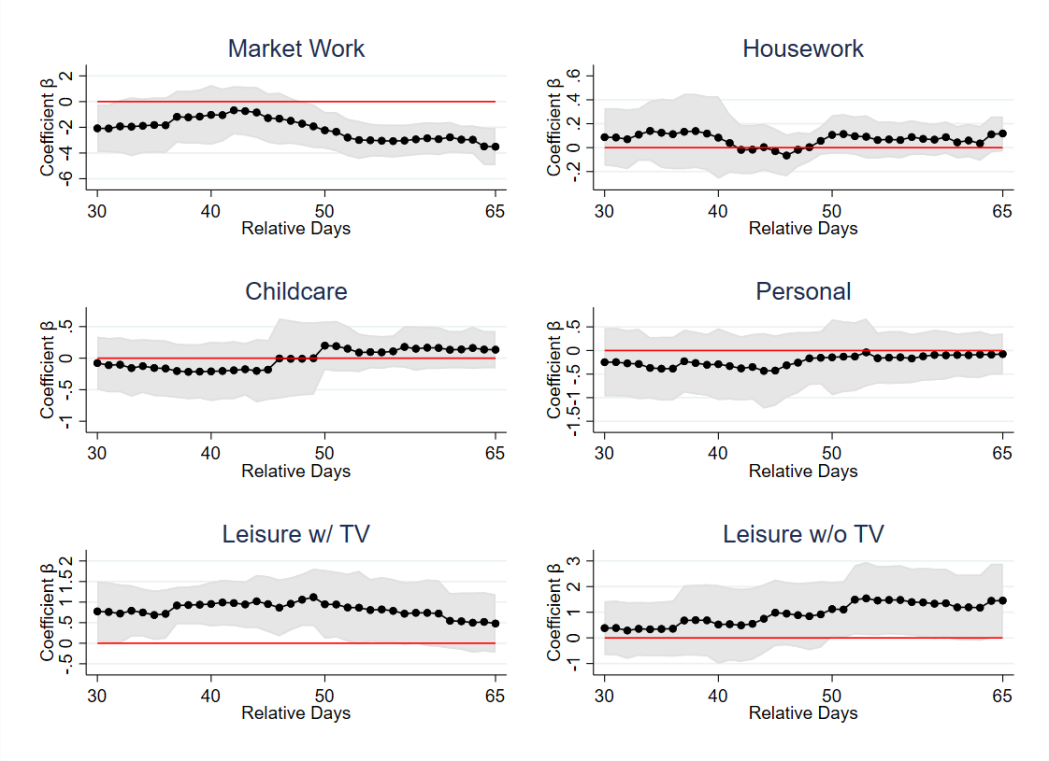

Figure 4.5: Dynamics of Time Reallocation for Males

Note: This figure plots the estimated coefficients of $Post \times Treatment$ against the relative days from the disaster for males. The shaded areas represent 95% confidence intervals of the corresponding coefficients. The analyses were conducted on the samples surveyed before the disaster and 30-day moving samples after the disaster.

4.4 Potential Mechanisms

Cognitive, motivational, and somatic consequences of a psychological shock could lead to a productivity decline (De Quidt and Haushofer 2016; Ridley et al. 2020). Indeed, economics (Banerjee and Mullainathan 2008; Oswald et al. 2015), neurobiology, and psychology literature (Dolan 2002) suggest a high association between mental health and productivity. As a series of papers document that the treatment group experienced severe stress (Yang et al. 2015; Han et al. 2017), we posit a model with a productivity drop upon a psychological shock and test its implications with the results.

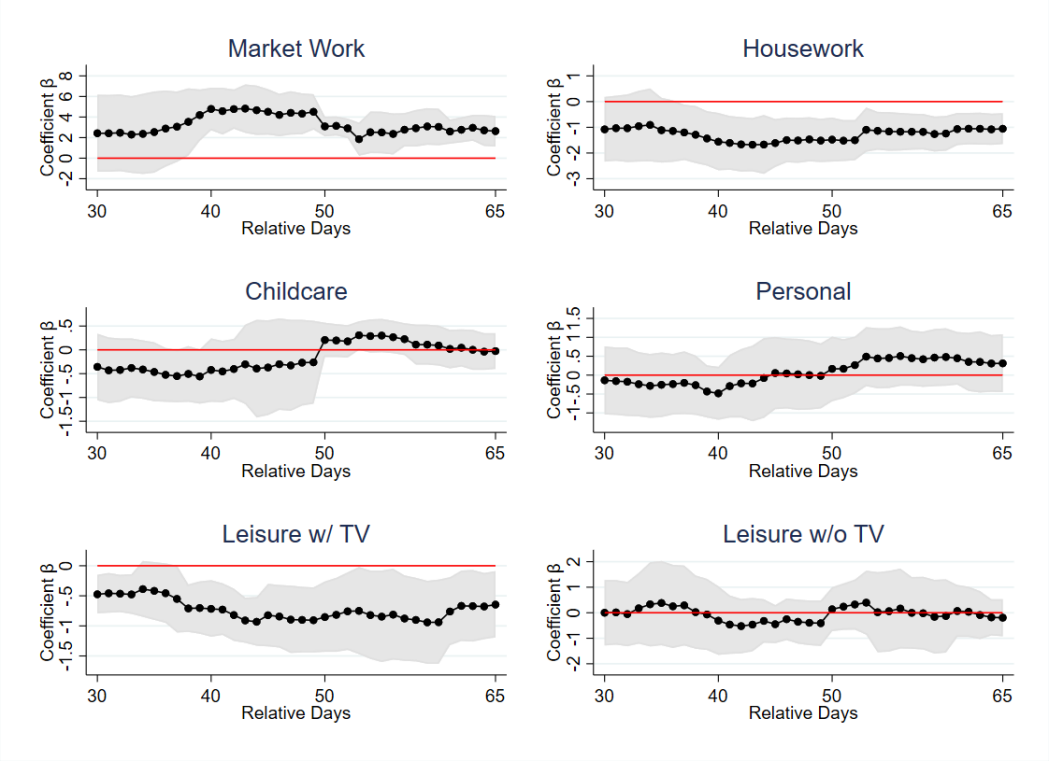

Figure 4.6: Dynamics of Time Reallocation for Females

Note: This figure plots the estimated coefficients of $Post \times Treatment$ against the relative days from the disaster for females. The shaded areas represent 95% confidence intervals of the corresponding coefficients. The analyses were conducted on the samples surveyed before the disaster and 30-day moving samples after the disaster.

To fix the idea, we introduce a model of time use adapted from Becker [1965]. Individuals maximize utility $U = U(X_M, X_H, L, s)$ with market goods X_M, home goods X_H, leisure L, and mental state s. We abstract away from other time uses to keep the model concise. The maximization problem is subject to resource constraint, $p \cdot X_M \leqslant f_M(T_M, s) + V$, home production function, $X_H = f_H(T_H, s)$, and time constraint, $T_M + T_H + L = T$, where p is a vector of market goods prices, $f_M(T_M, s)$ is piece-rate earnings, $w \cdot T_M$, for workers with hourly wage w, V is other sources of income, and T is time endowment. Concavity is assumed for both home production and market production functions. We assume piece-rate wage for market work as many contracts have either hourly, daily piece-rate, or fixed monthly salary structure.

The direction of time use adjustments could be predicted by deriving the equilibrium time use conditions. Assuming interior solutions, the pre-shock equilibrium condition could be characterized by the following equations:

$$\frac{\partial U(X_M, X_H, L, s)}{\partial X_H} \cdot \frac{\partial f_H(T_H, s)}{\partial T_H} = \frac{1}{p_i} \cdot \frac{\partial f_M(T_M, s)}{\partial T_M} \cdot \frac{\partial U(X_M, X_H, L, s)}{\partial x_{mi}} \qquad [5]$$

$$\frac{\partial U(X_M, X_H, L, s)}{\partial X_H} \cdot \frac{\partial f_H(T_H, s)}{\partial T_H} = \frac{\partial U(X_M, X_H, L, s)}{\partial L} \qquad [6]$$

where p_i is the price of a good x_{mi}. Equation [5] boils down to the following equation for workers with piece-rate wage w:

$$\frac{\partial U(X_M, X_H, L, s)}{\partial X_H} \cdot \frac{\partial f_H(T_H, s)}{\partial T_H} = \frac{w}{p_i} \cdot \frac{\partial U(X_M, X_H, L, s)}{\partial x_{mi}} \qquad [7]$$

This implies that the marginal utility of time use should be the same for market work, home production, and leisure.

With a psychological shock, the mental health gets worse from s to s_{Low} and the pre-shock equilibrium condition does not hold anymore as $\frac{\partial f_H(T_H, s_{Low})}{\partial T_H} \leqslant \frac{\partial f_H(T_H, s)}{\partial T_H}$. The individual adjusts his/her time use by reducing home production with the constant piece-rate wage w. Leisure would be a natural substitute after reducing home production unless there is further incentive for market work. Individuals who worked for a family business or did not participate in the labor market before the disaster could be an exception as their wages would depend on their productivity. The core results do not change even when we consider the case where the marginal utility of leisure depends on the mental state s. If individuals use leisure as a coping mechanism to the trauma (Coleman and Iso-Ahola 1993; Kleiber et al. 2002), U would have a negative cross partial with leisure L and mental state s.

A change in preferences or beliefs may be a mechanism as the prediction of the model with a productivity decline does not fully explain the results. The disaster had bidirectional shifts in working hours for males. As family business workers reduced working hours even further, the evidence suggests that non-self-employed workers mainly increased working hours after the disaster. Assuming that the wage does not immediately change, the model does not provide an explanation for why an individual would increase market work with constant wages. In addition, the increase in female market work was more substantial for the ones with a school-age child in their households. For females, market work may have been harnessed as a distraction to cope with the disaster. While it is difficult to rule out the productivity channel, preferences or beliefs channel is required to explain major time use adjustment results (Cameron and Shah 2015; De Quidt and Haushofer 2016; Ridley et al. 2020).

4.5 Conclusion

This paper examines how individuals re-allocate their time use with an exogenous psychological shock from the *Sewol* ferry disaster. Using the temporal and spatial variation of the disaster, we employ before-after and difference-in-differences methods to estimate the causal effects of psychological shock on time use. The disaster led the treatment group males to decrease market work and increase housework and leisure. For females, the disaster increased market work, leisure without a TV, and decreased housework and leisure with a TV. The kernel density distribution of market work before and after the disaster suggests that there were bidirectional shifts toward both zero and ten hours for both genders. The evolution of the effects suggests that most of the effects were lasting until the end of the sample period.

This study makes three contributions to the growing literature on the economics

of mental health. First, this paper provides the first evidence on the causal impact of a psychological shock on time use. Second, this study complements the theoretical works to explain the economic effects of mental health (De Quidt and Haushofer 2016; Ridley et al. 2020). Examining the effects of an exogenous one-time psychological shock directly speaks to the existing economic theory of mental health (De Quidt and Haushofer 2016). As time is one of the most primitive forms of resources, studying time use is important in understanding economic behaviors. Third, this paper documents the immediate evolution of the treatment effects on time use. Estimating the evolution is important in policy design. The fact that the treatment effects were persistent throughout the end of the sample period suggests that policy interventions toward the general population around the center of the disaster may be helpful. *Ansan Mental Health Trauma* center was set up 15 days after the disaster by the South Korean government, the center was mostly for the targeted populations such as victims and school-aged teenagers. The evidence suggests that it may be effective to extend the target population to the residents of the affected areas.

Chapter 5

Conclusion

This dissertation focuses on the socio-economic consequences of man-made disasters. Each chapter of this dissertation takes unique natural experiments to complement each other in understanding the short- and long-term, intergenerational, and immediate effects of man-made disasters on labor market outcomes, preferences, and time use. In all three chapters, the disasters lead to significant and meaningful effects.

Chapter 2 examines the ten-year evolution of the effects of the end of a man-made disaster, the Aceh Insurgency. In specific, I document that individuals adjust their labor market activity to conflict-free environments after the end of the Aceh Insurgency. It is surprising that the post-conflict economy quickly converges to a new equilibrium within two years after the end of the Aceh Insurgency and does not significantly change over the next 8 years. While the adjustments to the conflict-free environment imply that the post-conflict labor market activity would resemble the pre-conflict labor market activity, data limitations restrict comparing the post-conflict and pre-conflict labor market activity and economic environment.

Chapter 3 studies the intergenerational effects of a man-made disaster, the Korean War. Specifically, we explore how early life shock leads to intergenerational effects on preferences. It is intriguing that the effects of exposure to the Korean War between 4 and 8 have the opposite effects on mothers and sons. We conclude that parent-child attachment is a key mechanism underlying the opposite effects on mothers and sons by examining parent-child dyads and eliminating other potential mechanisms. While the evidence suggests the importance of nurture as nature would make the effects

similar on parent and child, the interaction between nature and nurture needs to be further explored.

Finally, chapter 4 examines the immediate effects of a man-made disaster, the *Sewol* ferry disaster. In particular, we investigate how a psychological shock affects time use. After the disaster, males substituted market work for leisure and females substituted housework for market work and leisure without TV. The substitutions are interpreted as coping mechanisms. As poor mental health has been shown to have negative socio-economic consequences in the literature, understanding how individuals adjust their time use to an exogenous psychological shock is fundamental to understanding the mechanism behind it. Since chapter 4 only documents the immediate effects, more work is needed to fully understand the mechanism.

Appendix - Additional Tables and Figures

Table A1: Alternative Treatment Group

	Male	Female
	(1)	(2)
Panel A: Work (Extensive)		
Peace × Any Homicide	-0.00	-0.13***
	(0.02)	(0.04)
Baseline mean	0.91	0.25
Observations	3,753	4,007
Panel B: Working Hours (Intensive)		
Peace × Any Homicide	3.96**	1.77
	(1.72)	(2.36)
Baseline mean	42.23	32.33
Observations	3,246	816
Panel C: Housework		
Peace × Any Homicide	0.00	0.13***
	(0.01)	(0.04)
Baseline mean	0.01	0.71
Observations	3,753	4,007

Note: This table reports the coefficient estimates of equation [4], regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A2: Coefficient Estimates After Adjusting for Pre-Trends

	Male (1)	Female (2)
Panel A: Work (Extensive)		
Peace × Rural	[-0.10, 0.04]	[-0.21, -0.09]
	(0.02)	(0.03)
Panel B: Working Hours (Intensive)		
Peace × Rural	[1.84, 3.06]	[2.78, 4.38]
	(1.56)	(1.83)
Panel C: Housework		
Peace × Rural	[-0.04, 0.04]	[0.04, 0.22]
	(0.01)	(0.03)

Note: This table reports the sets of coefficient estimates of equation [4] after adjusting for the pre-trends in figures A1 and A2. The difference of the maximum and minimum difference in the pre-trends between the treatment and control groups is employed as a possible violation of parallel trends Δ. Standard errors in parentheses are taken from the original estimates in table 3.2.

Table A3: Spillover Effects on Wages and Household Welfare

	Male (1)	Female (2)
Panel A: Expenditure		
Peace × Rural	-0.10	-0.11
	(0.09)	(0.07)
Peace × Spillover	-0.19	-0.31
	(0.16)	(0.19)
Observations	3,753	4,007
Panel B: Proportion of Food		
Peace × Rural	-1.98	-1.91
	(2.11)	(1.80)
Peace × Spillover	2.02	1.83
	(3.45)	(4.10)
Observations	3,753	4,007
Panel C: Wages		
Peace × Rural	-0.14	-0.57
	(0.71)	(0.43)
Peace × Spillover	0.58	0.32
	(0.79)	(1.05)
Observations	803	282

Note: This table reports the coefficient estimates of equation [4] with spillover effects, regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, the interaction term between *Peace* and *Rural*, the indicator *Spillover* for the communities adjacent to the treatment group, and the interaction term between *Peace* and *Spillover* along with age and year-by-month fixed effects. The extreme 5% of wage data is winsorized on each tail. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A4: The Short-Run Effects of Peace on Migration

	Male	Female
	(1)	(2)
Panel A: Migrated from the birth community		
Peace × Rural	0.00	-0.01
	(0.03)	(0.03)
Panel B: Migrated from the baseline community		
Peace × Rural	0.00	0.01
	(0.04)	(0.04)
Observations	3,753	4,007

Note: This table reports the coefficient estimates of equation [4] with migration indicators as the outcome variables, regressing the migration indicators on the post-conflict period indicator *Peace*, the treatment group indicator *Treatment*, and their interaction term along with age, year-by-month, and the baseline during-conflict household fixed effects. Panel A takes migration from the community of birth as the outcome variable, and panel B considers migration from the during-conflict baseline wave community as the outcome variable. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A5: Heterogeneous Effects of Peace

	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A: Work (Extensive)				
Peace × Rural	-0.01	-0.12**	-0.04	-0.17***
	(0.03)	(0.05)	(0.02)	(0.03)
Peace × Group	0.04	0.00	-0.05**	0.01
	(0.04)	(0.05)	(0.02)	(0.04)
Peace × Rural × Group	-0.02	-0.05	0.02	0.07
	(0.04)	(0.05)	(0.03)	(0.04)
Panel B: Working Hours (Intensive)				
Peace × Rural	-0.25	-1.39	2.41	3.73**
	(2.95)	(3.42)	(1.64)	(1.56)
Peace × Group	-2.52	-6.72**	0.39	2.21
	(2.56)	(3.25)	(2.08)	(2.83)
Peace × Rural × Group	3.27	5.26	0.11	0.25
	(2.83)	(4.11)	(2.32)	(3.05)
Panel C: Housework				
Peace × Rural	-0.01	0.14**	-0.00	0.14***
	(0.01)	(0.05)	(0.01)	(0.03)
Peace × Group	-0.00	0.05	-0.00	-0.04
	(0.01)	(0.05)	(0.01)	(0.04)
Peace × Rural × Group	0.01	0.01	0.01	-0.04
	(0.01)	(0.05)	(0.01)	(0.04)
Group	Primary School		Under 5 Child	

Note: This table reports the coefficient estimates of equation [6], regressing the labor market outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, the interaction term between *Peace* and *Rural*, the indicator for the group of interest *Group*, and the interaction term between *Peace*, *Rural*, and *Group* along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A6: 1st Generation Replication by Gender

	(1)	(2)	(3)	(4)
Risk preference parameter				
Panel A. in-utero to age 0				
$age^{inutero-0} \times RArea$	-0.15	-0.13	-0.15	-0.14
	(0.63)	(0.60)	(0.49)	(0.48)
Panel B. age 1 to 3				
$age^{1-3} \times RArea$	-0.20	0.05	-0.20	0.02
	(0.19)	(0.62)	(0.23)	(0.76)
Panel C (Main). age 4 to 8				
$age^{4-8} \times RArea$	-0.01	0.19**	-0.00	0.18***
	(0.96)	(0.03)	(0.97)	(0.01)
Panel D. age 9 to 13				
$age^{9-13} \times RArea$	0.06	0.08	0.08	0.05
	(0.73)	(0.64)	(0.59)	(0.76)
Sample	Male	Female	Male	Female
Sample age	20-85		50-85	
Number of observations	4,760	5,129	1,516	1,829

Note: This table replicates Kim and Lee [2014] by gender. Columns (1) and (2) takes the sample of age 20-85, the same as in Kim and Lee [2014]. In columns (3) and (4), the sample of age 50-85 is included to better resemble the age range of parents. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A7: Estimation of risk parameter using different age groups

	(1)	(2)	(3)	(4)
Risk preference parameter				
$mage^{inutero-0} \times RArea^m$	0.19			
	(0.39)			
$fage^{inutero-0} \times RArea^f$	-0.19			
	(0.40)			
$mage^{1-3} \times RArea^m$		0.07		
		(0.61)		
$fage^{1-3} \times RArea^f$		0.11		
		(0.59)		
$mage^{4-8} \times RArea^m$			-0.21**	
			(0.04)	
$fage^{4-8} \times RArea^f$			-0.13	
			(0.25)	
$mage^{9-13} \times RArea^m$				0.23**
				(0.05)
$fage^{9-13} \times RArea^f$				-0.11
				(0.51)
Number of observations	3,062	3,062	3,062	3,062

Note: This table reports the structural coefficient estimates of equation [3] using (Holt and Laury 2002) with alternative sensitive age groups as in Kim and Lee [2014]. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A8: Reduced-form estimates without choices 3 and 4

	(1)	(2)	(3)	(4)	(5)	(6)
$mage^{4-8} \times RArea^m$	-0.07*		-0.06		-0.07*	
	(0.06)		(0.21)		(0.07)	
$mage^{4-8} \times Intensity^m$		-0.75		-0.59		-0.71*
		(0.14)		(0.28)		(0.10)
Sample	Basline		Including no parents info as control		No migrant parents of treatment group	
Number of observations	3,062	3,062	2,646	2,646	6,841	6,841

Note: This table replicates table 3.6 with the proportion of safe choices excluding choice experiments 3 and 4 as the outcome variable. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A9: Short-Run Effects of Peace on Household Composition for Couples

	Household Size	Number of HH Males 20-64	Number of HH Members 0-4	Mean HH Adult Height
	(1)	(2)	(3)	(4)
Panel A: Male				
Peace × Rural	0.29***	0.01	0.10**	-0.07
	(0.08)	(0.02)	(0.04)	(0.06)
Sample size	1,386	1,386	1,386	1,383
Panel B: Female				
Peace × Rural	0.28***	0.02	0.10**	0.05
	(0.07)	(0.03)	(0.04)	(0.10)
Sample size	1,386	1,386	1,386	1,383

Note: This table reports the coefficient estimates of equation [4], regressing the household composition outcomes on the post-conflict period indicator *Peace*, the treatment group indicator *Rural*, and their interaction term along with age, year-by-month, and individual fixed effects. Standard errors in parentheses are clustered on the during-conflict baseline wave community. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A10: Estimation of risk parameters and reduced-form DID coefficients for parents-offspring dyads

	Structural estimate		Reduced-form estimate	
	(1)	(2)	(3)	(4)
$mage^{4-8} \times RArea^m \times Male$	-0.28**	-0.26**	-0.10**	-0.08
	(0.03)	(0.05)	(0.04)	(0.18)
$mage^{4-8} \times RArea^m \times Female$	-0.11	-0.09	0.01	0.02
	(0.30)	(0.43)	(0.91)	(0.75)
$fage^{4-8} \times RArea^f \times Male$	-0.08	-0.03	-0.04	-0.03
	(0.51)	(0.83)	(0.18)	(0.46)
$fage^{4-8} \times RArea^f \times Female$	-0.18	-0.17	-0.07	-0.08
	(0.28)	(0.37)	(0.43)	(0.47)
Sample	Baseline	No mover	Baseline	No mover
R squared	-	-	0.07	0.07
Number of observations	3,062	2,646	3,062	2,646

Note: Columns (1) and (2) reports the estimated structural risk aversion parameter of triple interaction term of the indicator variable for each parent-offspring dyad. Columns (3) and (4) reports estimates from reduced-form DID equation for each parent-offspring dyad. Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table A11: Behavioral impact of parental trauma exposure

Dependent Variable	Self-employed		Ever Self-employed	
	(1)	(2)	(3)	(4)
$mage^{4-8} \times RArea^{m}$	0.06	-0.12	0.08	-0.15
	(0.63)	(0.28)	(0.57)	(0.13)
Sample	Male	Female	Male	Female
Number of observations	853	486	853	486

Note: This table reports reduced-form estimates from equations (4) and (5) with current self-employment and life-time self-employment status as outcome variables.Wild bootstrapped p-values in parentheses(Kline and Santos 2012), which are clustered on province of birth. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

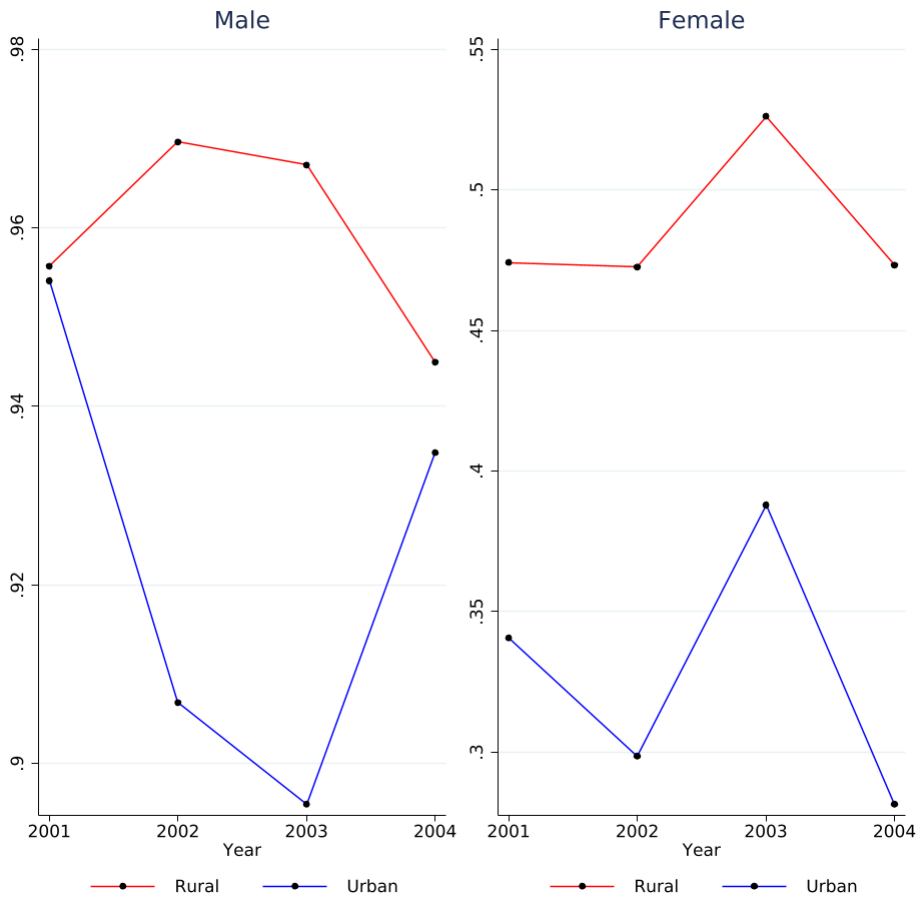

Figure A1: Pre-Trends of Work (Extensive Margin)

Note: This figure shows the trends of work for males on the left-hand side and for females on the right-hand side from 2001 to 2004. The red and blue lines are for the treatment and control groups, respectively. The x-axis indicates the calendar year, and the y-axis indicates the average value of work. The National Labour Force Survey (SAKERNAS) is used to calculate the sample average.

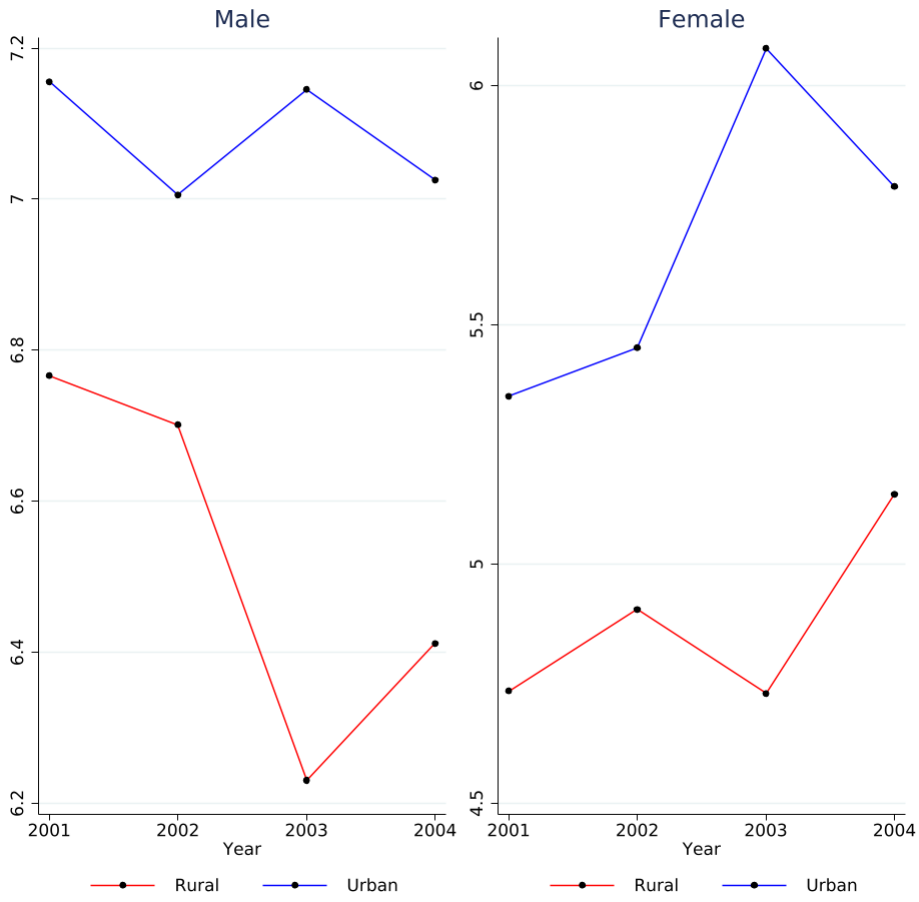

Figure A2: Pre-Trends of Working Hours (Intensive Margin)

Note: This figure shows the trends of working hours for males on the left-hand side and for females on the right-hand side from 2001 to 2004. The red and blue lines are for the treatment and control groups, respectively. The x-axis indicates the calendar year, and the y-axis indicates the average value of work. The National Labour Force Survey (SAKERNAS) is used to calculate the sample average.

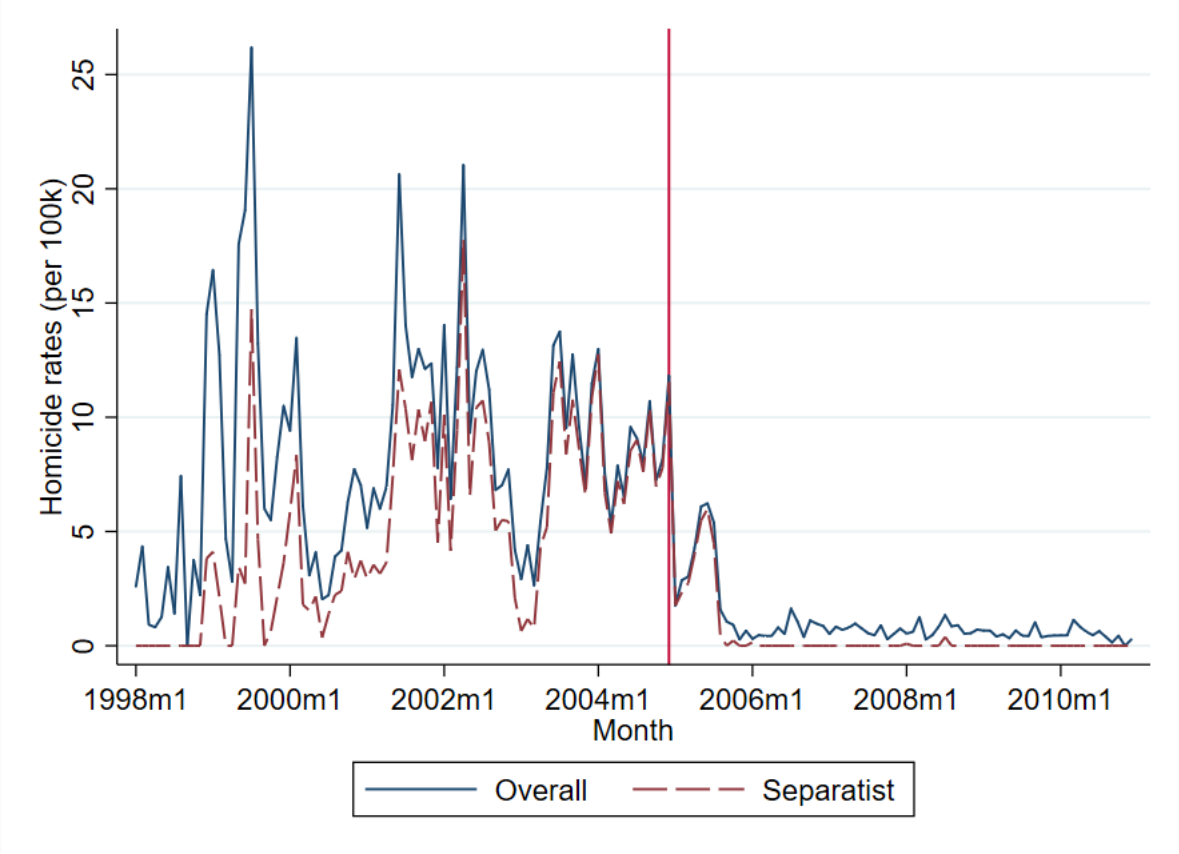

Figure A3: Trends of Homicide Rates

Note: This figure shows the overall and separatist-related homicide rates from 1998 – 2010. The x-axis indicates the calendar date. The vertical line marks the date of the 2004 Indian Ocean tsunami and earthquake. The National Violence Monitoring System (NVMS) and PODES 1996, 2000, 2003, 2005, 2008, and 2011 waves are used for the figure.

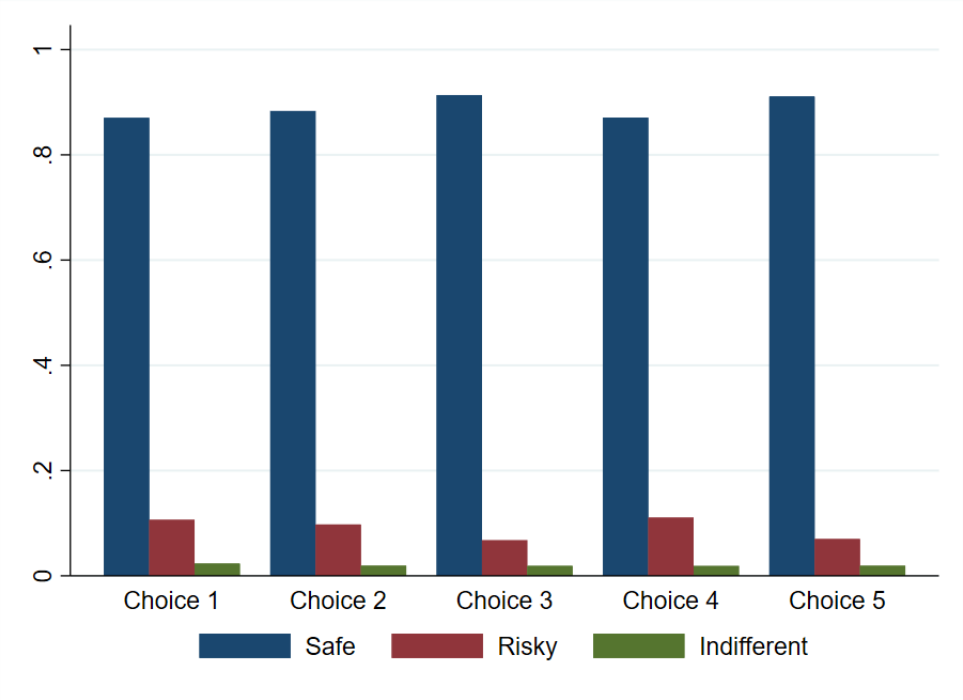

Figure A4: Choice experiment distribution

Note: This figure shows the choice experiment distribution. X-axis indicates the number of experiment. Y-axis shows the proportion of safe, risky, and indifferent choices in blue, red, and green colors.

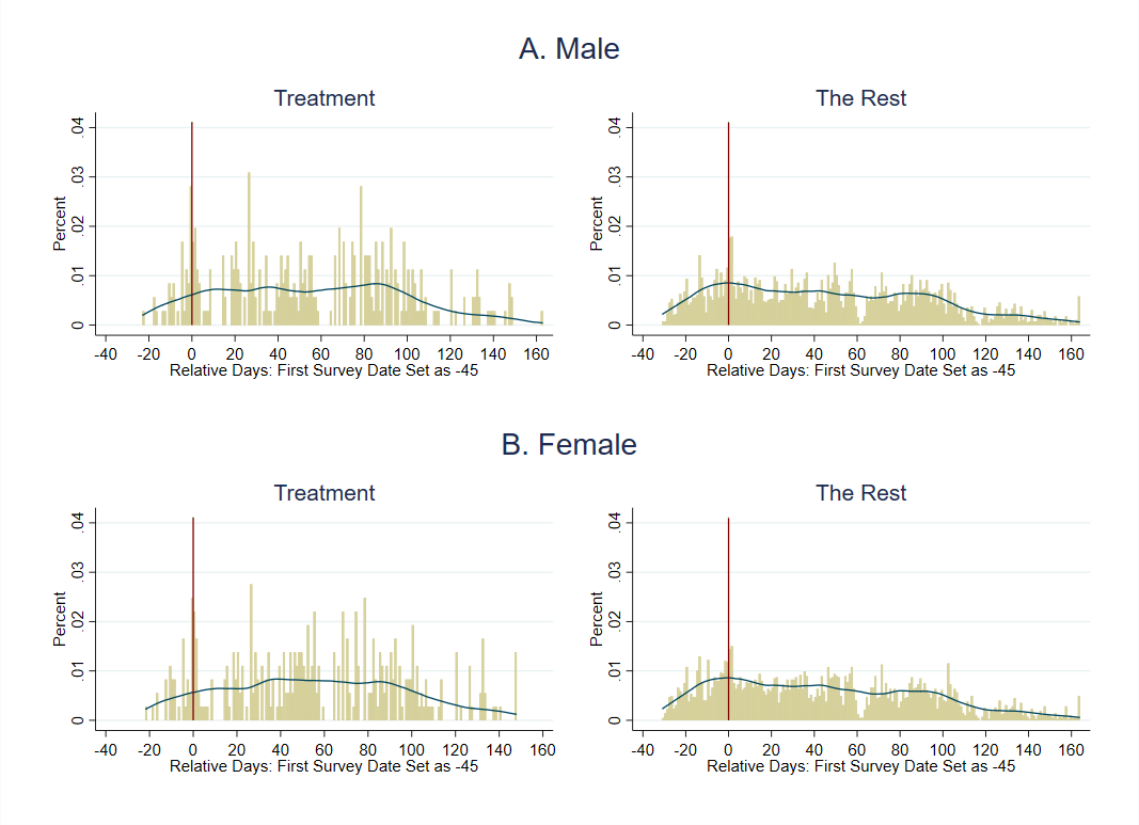

Figure A5: Distributions of observations by relative days - KLIPS 2013

Note: The left panels show the distributions of the number of observations for the treatment group while the right panels show the distributions for the rest of South Korea. The day of first survey was 45 days before the disaster in KLIPS 2014, thus we assigned -45 as the first day of survey in KLIPS 2013. The x-axis is the relative day from the45 days after the first survey. The y-axis is the percent of observations surveyed per day.

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Biography

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