The Allocation of Time after Psychological Shock: Evidence from the Sewol Ferry Disaster

Sok Chul Hong
Seoul National University

Dongyoung Kim
Duke University

[Preliminary]

Abstract

Using difference-in-differences method with the exact time use reference date as a proxy for the exposure to *Sewol* disaster, we estimate how people in the treatment region re-allocate their time in front of disaster, psychological shock in particular. Expanding time window from 7 to 65 days, we observe stable progression of treatment effect as the decrease in home production and increase in leisure. The neighboring region of the treatment group increased market work by sacrificing leisure. This is the first study of disaster's effect on time use and this may explain the mechanism behind macro consequences of disaster.

Keywords: Sewol ferry sinking, Time use, Disaster, Trauma, Growth.

1. Introduction

What determines the allocation of time is a fundamental question of economics in that time is the most primitive form of capital we have. With economic development, all resources except time get abundant and the relative price of time seems to be ever-increasing. At the same time, the number of disasters is expected to increase and so does the reach of disaster as a result of advancing media and information technology (terrorism for The Heritage Foundation 2016; natural disasters for IPCC 2013; civil war for Blattman and Miguel 2010). Therefore, how individuals re-allocate their time in front of disaster is an intriguing question of particular importance.

From the seminal paper of Becker (1965), increasing number of studies has been conducted on time use. Among others, some papers investigated individuals' time re-allocation in front of shocks. For instance, Gelber and Mitchell (2012) examined the tax shocks in the U.S. and Lee et al. (2012) documented change in time use in the wake of institutional permanent decline in market work. Hamermesh (2002) explored how people respond with foreknown extra free time, and Jacobsen and Kooreman (2005) structurally estimated the effect of relaxation of shopping hour regulation.

Though the effect of several shocks to time use has been investigated, no study has addressed how people re-allocate their time use in front of disaster. Presumably the lack of appropriate data has impeded it, even with the importance of studying time use. Traditional obstacles in the disaster literature such as selective migration, ambiguous treatment status or selective treatment would be major obstacles as well. Further, property loss from disaster would make the affected devote their time to make up such loss. Separating time re-allocations coming from psychological shock and property damage is crucial and difficult as most of disasters entail both.

Time re-allocations in the wake of disaster could be answered by the *Sewol* ferry sinking, the effect of the disaster-induced trauma in particular. The sinking occurred on April 16, 2014 near the southern coast of Korea. The ferry completely sank after 52 hours from the first distress call, and it is estimated that 304 passengers were lost out of 476 passengers. This is one of the biggest maritime disasters in Korean history. The sinking was so disastrous that not only domestic media was flooded with up-to-date information on the rescue operations of the passengers but also many foreign media broadcasted its severity. Its impact on the vicinity of *Ansan-si* was expected to be particularly significant as most of the victims from the disaster were concentrated in *Ansan-si*.

In this paper, we aim to shed light on how people re-allocate their time in the face of disaster, especially the psychological shock. The *Sewol* disaster is unique since victims are concentrated in one region without any property loss, which enable us to disentangle the psychological effect from the total effect. Using new data of time use with the exact time use reference date as a proxy for the exposure to the sinking, we establish causal relationship between disaster-induced trauma and time use for those residing in the treatment region, the vicinity of *Ansan-si*. Expanding bandwidth from 7 to 65 days from the sinking, we examined the evolution of the treatment effect. We find that people in and around the *Ansan-si* (*Tier1*) spend less in home production and more in leisure1, and the progression of estimated treatment effects is stable. On the other hand, *Tier2* (the neighboring region of *Tier1*) increased market work, whose progression fits the reversed pattern of the progression of decreases of home production in *Tier1*.

Our findings have two distinct implications. First, the interaction between the treated region (*Tier1*) and its neighboring region (*Tier2*) may explain how economic growth is not negatively affected by disasters in the long run even with its long-lasting damage on human capital accumulation. Second, the estimated treatment effects are derived from the pure psychological effects as the disaster entailed no direct property loss to the individuals in treatment region besides to the family of the victims. As disaster also affects people in other countries (Metcalfe et al. 2011), estimating the cost of psychological shock is particularly important. Indeed, the effect of trauma on time use would be more widespread with the progress of information technology.

In Section 2, we present review of relevant literature. Section 3 describes data and variables. We show empirical results in Section 4, provides some discussion in Section 5. Finally, Section 6 concludes.

2. Literature Review

Literature on the allocation of time has been expanding. As time use is one of the fundamental sources of socioeconomic outcomes, the importance of studying time use is self-explanatory. Since the seminal paper of Becker (1965), studies on time use is broadening its scope. Not to mention that the determinants of time allocation have been examined, such as aggregate fluctuations (Aguiar et al. 2013) and institutional factors (Krueger and Mueller 2010, 2012; Guler and Taskin 2013). Evolution of time use also has been inspected including time use over time (Aguiar and Hurst 2007a; Ramey and Francis 2009) and over life cycle (Aguiar and Hurst 2007b). Excellent review of recent advance in time use literature can be found in Aguiar et al. (2012).

Some papers addressed people's time re-allocations in response to shocks. Gelber and Mitchell (2012) examined the relationship between taxes and time use. Panel Study of Income Dynamics as primary data, they examined time re-allocations caused by changes in taxes: upon decline in taxes, market work increased and home production decreased. Lee et al. (2012) documented change in time use in the wake of institutional permanent decline in market work. Time diary surveys from Japan and Korea displayed within-person increase in leisure and personal maintenance, respectively. Hamermesh (2002) found that (foreknown) increase in free time goes to sleeping and Jacobsen and Kooreman (2005) structurally explored the effect of relaxation of shopping hour regulation.

Another strand of literature relevant to this paper is the studies on disaster. Disaster-induced behavioral response and preferences change are often identified. For example, Berlemann et al. (2015) investigated the influence of 2002 Flood in Saxony on saving behavior. Their difference-in-difference (DID) estimates suggested reduction in both saving decision and the amount of savings by the sinking. Disaster-induced shifts in preferences[1] were observed as well (e.g. Eckel et al. 2009; Voors et al. 2012; Reynaud and Aubert 2014; Callen 2015; Imas et al. 2015). Cassar et al. (2011) showed increase in risk-aversion and impatience among those severely exposed to 2004 Asian tsunami. Similarly, Cameron and Shah (2015) found that the recent exposure to natural disasters lead to higher levels of risk-aversion. In the long-term

[1] Although there is a vast literature regarding other preferences such as social preference, we exclude those since they seem to be irrelevant to our findings.

perspective, DID estimates of Kim and Lee (2014) indicated that those who exposed to the Korean War at age 8-12 are more risk-averse after about five decades from the sinking.

Literature consistently reports that disasters cause lasting negative impacts on human capital accumulation. Ichino and Winter-Ebmer (2004) studied educational cost of World War II. With DID, they found that Austrian and German civilian-inflicted cohorts of age 10 around the time of conflict had significantly lower educational attainment and earnings. Analogously, with Peru's civil conflict, León (2012) estimated that exposure to violence in early childhood considerably reduced years of education. Their DID estimates were robust to the inclusion of sibling fixed effects. Grimad and Laszlo (2014) identified that Peru's civil conflict also negatively affected an indicator of long-term health, height, for female sample.

Relevant to our study, stress from disasters leads to such negative impacts on human capital accumulation as well. Currie and Rossin-Slater (2013) found that stress from hurricanes cause abnormal conditions and complications of labor, which is an early indicator of later human capital. Exploiting 1970 Ancash Earthquake in Peru, Caruso and Miller (2015) identified that stress from the sinking inflicted the affected fetuses' and their offspring's socioeconomic outcomes. In a similar vein with 1974 Super Tornado Outbreak, Hong et al. (2016) investigated how fetal exposure affects first and second generations' socioeconomic outcomes. By eliminating alternative explanation for the results, they concluded that the stress from the disaster is the mechanism behind their findings.

Contrary to the literature on disaster's individual-level effect, whether disaster has long-run negative impacts on macroeconomic consequences are debatable. Skidmore and Toya (2002) utilized cross-country variation to identify the long-term impact of natural disasters. They found that climatic disasters promote growth while geological one stunt growth. While Berlemann and Wenzel (2015) reported lasting effects of drought on economic growth up to ten years from the sinking, many empirical findings support only short-run effects. For instance, Strobl (2011) found hurricanes have local negative effect on per capital income growth, which does not last long. Cavallo et al. (2013) employed synthetic control approach (Abadie et al. 2010) to construct more comparable counterfactual, and found only fleeting negative effect after accounting for political changes.

No paper has examined how people re-allocate their time use in the face of disaster, especially traumatic shock. Absence of such attempts primarily lies in the lack of appropriate data. Traditional obstacles in the disaster literature such as selective migration, ambiguous exposure status or selective exposure to the sinking would be major obstacles as well. Further, property damage from disaster would make the affected devote their time to compensate such loss. Thus, separating time re-allocations coming from psychological shock and property loss is crucial and demanding as most of disasters entail both. As time is one of the most fundamental determinants of socioeconomic outcomes, studying disaster-induced time re-allocation could shed light on the mechanism behind the consequences of disaster.

3. Data and Variables

Our primary data is the 17th wave of the Korean Labor Income Panel Study (KLIPS), which is a nationally representative annual longitudinal survey of South Korea. It contains information on demographic, socioeconomic variables with exact time use reference date, which can be harnessed as an indicator of the exposure to the sinking. For initial analysis, we include individuals who reported time use about between a week before and after the date of disaster. Since the exposure to the sinking is ambiguous at the very day of the disaster, we excluded those who referred time use on the day of the disaster. One week is set as initial bandwidth for two reasons: 1) attention to the sinking remained high for one week and plummeted thereafter[2]; 2) Silverman's Rule-of-Thumb bandwidth is about a week[3]. Because there could be systematic change in time use after retirement or before graduating high school, we restricted our sample to those between age 20 and 59. The remaining sample comprised of 1,241 observations. After eliminating samples with sum of time use less than the entire time endowment (67), missing covariates (67) and proxy-interviewed (63), our final sample consists of 1,044 individuals.

The *Sewol* ferry disaster occurred on April 16, 2014 near the southern coast of Korea. The ferry departed from Incheon on April 15th night to Jeju island, which was its regular schedule. On 16th morning, it made a sudden sharp turn near southern coast of Korea. By the

---

[2] According to Google Trend, the keyword *Sewol Ferry* was searched intensively until the seventh day from the day of the sinking.

[3] Silverman's Rule-of-Thumb suggested little above 6.5. Although most of the Regression Discontinuity (RD) literature under-smooth by setting bandwidth a bit smaller than the one from the Rule-of-Thumb, we proceed with one week bandwidth as we use RD only for robustness check.

turn, it began to list and capsize. It is still unclear why such an abrupt turn was made. Although one passenger made an emergency call for help after five minutes from the turn, the ship sank completely including its bow after 52 hours. This is one of the biggest maritime disasters in Korean history. It is estimated that 304 passengers were lost out of 476 passengers. Among the onboard passengers, 325 were high school students on their field trip from *Danwon* high school, which made the disaster more tragic. The sinking was so disastrous that not only domestic media was flooded with up-to-date information on the rescue operations of the passengers but also many foreign media broadcasted its severity[4].

As the victims of the *Sewol* disaster were concentrated in one region, *Ansan-si*, we expect those who live in and around the region to respond differently to the disaster. With this intuition, we include *Ansan-si* and its neighboring counties into the treatment group[5]. Specifically, we consider those living in *Ansan-si* and its contiguous the *si*-level counties (*Tier1*) who referred time use on date after the sinking as treatment group. We also examine the effect of disaster on the *Tier1*'s neighboring region (*Tier2*) as there might be some interaction between those regions. Finally, *Tier2*'s neighboring region (*Tier3)* is used for placebo test since there should be no or at least less effect from the disaster. Therefore, *Tier1* constitute treatment group, *Tier2* is considered as partially-treated, and the rest of the country is set as control group (see figure 1). Of course the disaster might as well affect the rest of the country, but *Tier1* is treated in the sense that the victims were concentrated in it and the sinking's distinct effect on *Tier1* is empirically supported by table A1. The dependent variables were originally surveyed with 30-minute interval for 16 categories. Following Aguiar and Hurst (2007a), we combined it into six categories[6]: market work, home production, leisure1, leisure2, leisure3, and leisure4.

---

[4] In a day, the news regarding the disaster was disseminated by several foreign media such as ABC, BBC, France 24, the New York Times, the Time magazine, USA today.

[5] Using distance from *Ansan-si*, we found that the treatment effect is not proportional to linear distance but to hyperbolic distance (see table A1 in the Appendix). Practically, one major reason for the choice of treatment group is sample size. As can be found in table 1, sample size is not large even with *Tier1* and thereby it would be difficult to secure reasonable inference with more narrowly-specified treatment group.

[6] Following Aguiar and Hurst (2007a), leisure1 is sum of leisure and meeting friends; leisure2 is sum of leisure1, sleeping, and personal care; leisure3 is sum of leisure2 and child care; leisure4 is sum of leisure3, self-improvement, religious time, and volunteering. We set market work as sum of commuting, primary work, secondary work, job-seeking, and meeting coworkers, while putting home production as sum of family care, housework, and family meeting.

[Figure 1 about here]

Descriptive statistics of our sample are present in table 1. We categorize our sample by whether it referred time use on after the sinking (*Sewol*) and whether it belongs to the treated region (*Tier1*). The third column becomes treatment group and column (4) – (6) constitute control group. While column (1) and (2) summarizes descriptive statistics of the entire sample with one-week window, column (7) presents p-value of difference in differences (DID) between (3) and (4), and (5) and (6). Figure 2 graphically shows the differences for one-month bandwidth. In line with table 1, control group has no jump with respect to the day of the sinking. Treatment group, however, shows decline in both market work and home production, and increase in leisure1 and 4, which is in line with table 1.

[Table 1 about here]

[Figure 2 about here]

Although self-reported health, the number of family members, and log of adjusted family income differ significantly, other covariates are well-balanced. As the disaster was unexpected and the KLIPS' sampling procedure is random in terms of the unbalanced covariates, it should be representative to analyze the impact of the sinking as long as the unbalanced variables are controlled. However, table 1 suggests two concerns regarding our sample: since self-reported health may reflect mental health, it might as well be a dependent variable than control variable; the most suffered from the disaster might have rejected to participate in the survey, which would lead our estimate to an underestimate of the true effect.

4. Result

4.1 Baseline Estimation

In analyzing how the *Sewol* disaster affects time use of the people from the treatment region, we employ difference-in-differences (DID) model:

$$Y_i = \alpha Sewol_i + \beta Sewol_i \times Tier1_i + \rho Tier1_i + X_i\Gamma + \delta_{province} + \varepsilon_i \qquad (1)$$

where Y_i represents various time use in hours a day, $Sewol_i$ is an indicator variable for those who referred time use on post-sinking dates. $Tier1_i$ is a dummy for indicating those who live in or around *Ansan-si*, and $Sewol_i \times Tier1_i$ is the interaction term of $Sewol_i$ and $Tier1_i$. X_i are demographic and socioeconomic covariates, and δ_{area} is the largest administrative province fixed effects. Further, by including the smallest-possible county fixed effects δ_{county} instead of $\delta_{province}$, $Tier1_i$ is absorbed into county fixed effects δ_{county}, and equation (1) could be summarized into equation (2):

$$Y_i = \alpha Sewol_i + \beta Sewol_i \times Tier1_i + X_i\Gamma + \delta_{county} + \varepsilon_i \qquad (2)$$

Here, the coefficient of interest is β as it measures the treatment effect of the sinking.

To increase credibility of our results, we employ regression discontinuity (RD) design as following:

$$Y_i = \alpha Sewol_i + \beta Sewol_i \times Tier1_i + \theta_1 S_i + \theta_2 S_i^2 + \tau_1 Sewol_i \times S_i + \tau_2 Sewol_i \times S_i^2 + X_i\Gamma + \delta_{county} + +\varepsilon_i \qquad (3)$$

The difference between (2) and (3) is the inclusion of S_i, S_i^2, indicating polynomials of relative date from the day of the sinking, and their interactions with $Sewol_i$. One week is set as baseline bandwidth for two reasons: 1) attention to the sinking remained high for one week and plummeted thereafter; 2) Silverman's Rule-of-Thumb bandwidth is about a week. As long as the assumptions of RD are maintained around the cutoff, the similarity of estimated β from (2) and (3) would support the treatment effect's causal relationship. Note that our estimates should be considered as of intent-to-treat because there could be some people who do not know about the sinking, though it is very unlikely due to the heavy media coverage. We use ordinary least squares and the standard errors are clustered at the province level.

Table 2 presents the estimates of β from the equations. As the composition of counties within *Tier1* differs by the survey schedule, we controlled county fixed effects within

Tier1 in panel A. The results are similar to the one with the inclusion of personal covariates and day-of-the-week effect in panel B. In panel C and D, we include province and county fixed effects, respectively, and the results are qualitatively similar. Although the inclusion of province fixed effects has almost no effect on the estimates, the inclusion of county fixed effects increases the treatment effect's magnitude and significance. We set the model in panel D as our baseline in that it controls as many confounders as the data allows. Robustness of DID estimate is tested in panel E with RD design. The estimates of β are almost identical between DID and RD, enhancing credibility of our identification strategy[7]. Further, our findings are robust to using tobit or excluding subjective health from control variable (not reported).

[Table 2 about here]

Magnitudes of treatment effects are considerable. Based on panel D, market work decreased and all leisure terms increased at least half of their standard deviations, albeit the effect on home production is rather small. Large contraction in market work is surprising in that it is difficult to re-allocate at the margin due to institutional limitation, and it does not seem to come from differential working status as mean employment rates are little larger in *Tier1* after the sinking. Therefore, this initial departure in market work may come from region-level arrangement or personal leave. It is not hard to imagine that companies might have temporarily reduced working hours to alleviate shocks from the sinking, as well as individuals taking a leave to compensate psychological shocks. Indeed, there has been an article reporting that many took a leave to volunteer to help the victims (Lill, 2014). On the other hand, home production declined about 17 percent of its mean. Among distribution of leisure time, leisure, meeting friends, and sleeping are dominant sources of the increase. The escalation of meeting friends is intuitive as the old saying "Sorrow shared is sorrow halved" and the expansion in sleeping is in line with Hamermesh (2002), which examined the response to windfall hour.

---

[7] We employed linear polynomial for RD due to short bandwidth. The coefficients of $Sewol_i \times Tier1_i$ are very similar even when we used quadratic polynomial.

4.2 Evolution of the Treatment Effect

As our data provides sufficient sample even after a week from the sinking, we can examine how the impact evolves as time passes. Loosely speaking, we try to examine cumulative impulse-response function of the treatment effect. For the analyses, we only report the DID results with increasing bandwidth. This is because RD design is reliable with local linear or quadratic polynomials (Gelman and Imbens 2014). Since the initial choice of the treated region (*Tier1*) is arbitrary, we run equation (2) and (3) by adding interaction of $Sewol_i$ and $Tier2_i$ (the neighboring region of *Tier1*):

$$Y_i = \alpha Sewol_i + \beta_1 Sewol_i \times Tier1_i + \beta_2 Sewol_i \times Tier2_i + X_i\Gamma + \delta_{district} + \varepsilon_i \qquad (4)$$

In order to avoid reporting results from too small sample size, we investigate the treatment effect up to 65 days from the disaster[8].

Evolution of the estimated β_1 and β_2 from equation (4) on market work and home production are reported in figure 3. Panel A and B shows the estimated β_1, and panel C and D presents the estimates of β_2. On the one hand, the effect of the sinking on market work of *Tier1* rapidly fades away to zero and becomes insignificant after 18th day from the sinking. This seems reasonable as the decrease in one-week bandwidth seems to come from regional arrangement or personal leave; companies may set the working hours back to pre-sinking level after mitigating the impending shocks, and individuals should get back to work. On the other hand, the disaster's effect reduces home production of *Tier1* persistently and it appears quite stable after about a month. Surprisingly, the progression of the increases in market work of *Tier2* is almost identical to the reversed pattern of declines in home production of *Tier1*, albeit the magnitude of increase in market work is greater than the decrease in home production.

[8] Up to 65 days from the sinking, there are 72 observations per day on average. However, there are only 20 individuals with no one residing in *Tier1* at 66th day from the sinking, which seems to be insufficient to get credible inference from (see figure A1). One possible concern is that relatively more individuals referred on between 50 and 65 days after the sinking in *Tier1*. This may suggest that the most severely-affected individuals deferred the survey until 50 days after the sinking. To be conservative, we considered 65 days after the sinking always with the 50 days after the sinking. Further, although the data spans only up to 45 days before the sinking, it would not matter as 45 days are long enough to provide the appropriate counterfactual.

[Figure 3 about here]

Home production could be defined by the elasticity of substitution between time and goods in the production (Aguiar and Hurst 2007a), which implies that they can be substituted from the market. The decrease in home production in the treated region, *Tier1*, would transfer into increased purchases in relevant goods. For instance, individuals in the treated region could employ visiting housekeeper as they reduce home production. We suspect that these goods could be supplied by the neighboring region (*Tier2*) as suggested by the figure3. Figure 4 and 5 plots estimates of β_1 and β_2 on leisure terms with increasing bandwidth. For *Tier1*, the magnitude of decrease in home production and the increase in leisure1 are about 20 percent of their standard deviation, respectively. That is, they crave in immediate delights the most, such as leisure or meeting friends, by reducing home production. Expansion of leisure1 is offset by decreases in other components of leisure terms, resulting in the short-lived effects of disaster on leisure2-4. Individuals in *Tier2* mainly reduced leisure2, whose magnitude is about 30 percent of its standard deviation, and the decrease persists up to leisure3 and 4. As 65-day bandwidth is the longest possible one regarding the corresponding sample size, we proceed our analysis with 65-day bandwidth hereafter[9].

[Figure 4, 5 about here]

4.3 Subgroup Analysis

The disaster may have differential effect with respect to the individual's demographic characteristics. To gain additional insight into the heterogeneous treatment effects we divide our sample with regard to age, education, and family income: specifically, younger cohorts (age 20 to 39) and older cohorts (age 40 to 59) as our sample includes individuals of age 20 to 59; the highly educated (college or above) and the less educated (high school graduates or below); the rich (above median family income) and the poor (below median income). Results

9 The results are broadly similar with the one from 55-day bandwidth.

are reported in table 3.

Regarding interaction between *Tier1* and *Tier2*, as providing substitutes of home production would not require strong cognitive and even physical ability, we assume that increase in such works is performed mainly by those having weak bargaining power in the labor market. For example, the old (over 40) or relatively less educated (less than college degree) would relatively increase their working hours. Indeed, the young (under 40) could earn higher wage with the same time input by engaging in the work requiring physical ability, and the educated could do the same by providing labor to the work requiring cognitive ability. These predictions for *Tier2* are realized in the table: both the older cohorts and the less educated increased market work relatively more than their counterparts. Therefore, *Tier2* appears to satisfy the increased needs of home-related goods in *Tier1*.

[Table 3 about here]

Other than that, in panel A, older treatment group decreased market work considerably and home production rather modestly. In contrast, younger treatment group increased market work and reduced home production. This may be due to the expected benefit of future career. As the old have fewer years to reap the returns from career, they can decrease market work without such concern. While older treatment group increase all leisure terms significantly, increase in leisure lost its significance for leisure3 and 4 for the younger counterpart. This would come from decline in child care, which seems to reflect the decrease in the expected value of raising a child. Further, the highly educated treatment group dominates the change in time use in panel B. The results seem to stem from the budget constraint of the less educated. Again, in line with the decline in the expected benefit of raising a child, both treatment groups decreased leisure3. In panel C, major source of labor supply is the poor among those in *Tier2*. For such adjustment, they primarily sacrificed leisure2 and 3. Contrary to the decrease in child care for the rich treatment group, the poor treatment group increased child care. Both treatment groups decreased home production and increased leisure1 precipitously. If the privileged subgroups in *Tier1*, the educated and the rich, increased leisure1 to cope with psychological shock from the sinking, responses of the unprivileged might reflect the lack of sufficient resources.

4.4 Timing of Re-allocations

One important question about time use is the timing that people re-allocate their time use. A priori, we expect the treatment group to avoid both market work and home production in evening and night after the sinking as it is unpleasant time to work (Hamermesh 1999, 2002). On the other hand, those living in *Tier2* are expected to increase market work by sacrificing leisure times. To investigate it, we categorized a day into morning (6:00~12:00), daytime (12:00~19:00), evening (19:00~22:00), night (22:00~6:00)[10]. Although people in *Tier2* worked more on morning and daytime by reducing leisure times throughout the day except night time, results in table 4 are a bit different from our expectation for those in *Tier1*. While market work decreased in evening, increased in morning time, and remained unaffected among other times, home production declined in all times but night. Differences between market work and home production would reflect the institutional limitation in that it is difficult to re-allocate working time or timing at the margin. Insignificant and small re-allocations in night time also can be explained by the fact that most of the night time is devoted to sleeping. There is not much time to re-allocate in the first place. Increases in leisure were concentrated in leisure1 along all times and leisure2 in daytime and evening. In the night, they seem to sacrifice leisure2 to increase leisure1. Overall, individuals in *Tier1* substituted home production with leisure, especially leisure1.

[Table 4 about here]

4.5 Robustness Check

It is natural to ask whether our treatment specification following geographic closeness is reasonable. According to our specification, closer to *Ansan-si*, the treatment effect should be stronger. To test this, we estimated the evolution of treatment effect with equation (4) by replacing the interaction of $Tier1_i$ with $Sewol_i$ by the interaction of $Tier1'_i$ with $Sewol_i$.

[10] It appears natural to set 6:00~12:00 as morning and 12:00~19:00 as daytime after we referred Hamermesh (2002) for setting 19:00~22:00 as evening and 22:00~6:00 as night.

Here, *Tier1'* is *Ansan-si* and the smallest-possible counties surrounding it. Those living in *Tier1* but not in *Tier1'* are excluded from the analyses as they seem to have been affected by the sinking. Even though the sample size of treatment group gets smaller with such choice, the evolution of the treatment effects is qualitatively identical with that of *Tier1* and quite substantial than that of *Tier1* (see figure A2, 3). This squares with our intuition.

To intensify the validity of our estimates, we ran two placebo tests. First, we ran equation (4) by adding interaction of *Tier3* with $Sewol_i$. *Tier3* represents the neighboring region of *Tier2*, so it is expected to get no or at least less effect from the sinking. In line with the intuition, there is practically no effect (see panel A, B of figure A5 and figure A6 for *Tier1* as treated region, and panel C, D of figure A5 and A7 for *Tier1* as treated region). Moreover, there might be some effect on those who reside in and around the southern coast of Korea, where the ferry capsized. Since there are too few observations around the southern coast, we were not able to run a regression with those living in the province. Instead, we ran equation (4) by excluding those living in the province. If there was an effect on the southern coast, estimates excluding them would depart from our original estimates. However, our estimates were robust to the exclusion (see figure A8, 9, 10).

5. Discussion

Now, a natural question dawns on us: what is the mechanism behind the disaster's effect on time use? Recent study of Callen et al. (2014) suggested a mechanism where disaster could change preferences from the psychological aspect. Through inducing subjects to recall fear, the authors found that the fear-related recollection with recent experience of violence increases preference for certainty. Incessant news about the disaster and its salience would provoke individuals to recall the sinking. Even when they deliberately ignore news, the victim school's name *Danwon* is the name of a county in *Ansan-si*. Our treatment group could reside in *Danwon* or frequently encounter people from *Danwon*, which would induce their recollection about the disaster. This is even more plausible given the spatial compactness of Korea. Such cues including news would act just same as Callen and his co-authors' fear-related question, which would make individuals pursue certainty.

In general, disaster-induced alteration in preferences along with increase in background risk may explain our results. Becker and Mulligan (1997) asserts that individuals can re-allocate their time discounting to maximize their utility. In the same reasoning, the sinking may have affected preferences such as increasing time preference or risk-aversion, and external cues could have enhanced it. Such preference adjustments sound reasonable as they update background risk higher by the sinking. Further, Reynaud and Aubert (2014) found that the disaster-induced increase in risk-aversion remained significant after taking account for the increase in background risk. They argue that behavioral modifications after disaster may be due to preference changes.

The existing literature also indicates that psychological shock has its own effect on preference. For example, some studies found that the effect of disaster on preferences was robust to the control of property damage (Cassar et al. 2011; Cameron and Shah 2015; Imas et al. 2015). By controlling such loss, the studies indirectly presented that the trauma from disaster make people risk-averse, impatient, and present-biased, which is in line with the present-oriented change in time use. Of course, the effect of the increase in background risk is ambiguous as it could affect risk-attitudes in both directions depending on the individual preferences structure (Gollier and Pratt 1995, Quiggin 2003). However, many experimental papers support that the increase in background risk make people more risk-averse (e.g. Harrison et al. 2007, Beaud and Willinger 2013). Therefore, in this paper we step aside from the issue. Although we can neither confirm nor refute exact mechanism with our data, we hope this paper stimulates future research to identify the mechanism behind our findings.

This paper makes several implications and contributions to the literature. First and foremost, the fact that treatment group decreased home production with increasing leisure1 and the people around the treatment group increased market work by reducing leisure suggests possible mechanism behind macro effects of disaster. For example, Cavallo et al. (2013) found that disasters disturb growth only temporarily. If the victims of disasters did not reduce their market work and the people in the treatment region increased market work, it is not surprising that disasters have only fleeting effect. Further, this shed light on why growth is not stunted even with the long-lasting damage on human capital accumulation against growth. Our findings suggest that the decreased growth capacity could be offset partly by the increase in market work from the adjacent regions.

Second, this is the first study investigating how disaster alters time allocation, notably the psychological shock. Studying the allocation of time is meaningful by itself in that time is the most primitive form of capital we have. With economic development, all resources except time get abundant and the relative price of time seems to be ever-increasing. As the number of disasters increases and so does the reach of disaster as a result of media, how individuals re-allocate their time in the wake of disaster is an intriguing question of particular importance. Especially, because people in the other country (Metcalfe et al. 2011) get indirectly affected by the media, the fact that we could estimate the effect of pure trauma on another aspect is noteworthy.

Third, the precipitous increase in leisure1 may have some implications on the welfare effect of disaster. It has been shown that individual mental health and subjective well-being are inflicted by disaster (Rehdanz et al. 2015; Kim and Kim 2016). We have observed that socioeconomically privileged groups, the highly educated and the rich, increased their leisure1 more substantially than their counterparts. If they compensate the psychological shock from the disaster by enjoying more leisure1, our results suggest that the less privileged may not be able to compensate such shocks as much as the privileged presumably due to resource constraint. This could imply decrease in such individuals' welfare.

Fourth, heavy media coverage with provoking expressions should be restricted. Callen et al. (2014) have shown that the cues for recollection of fearful memory could cause preference changes. Ceaseless and agitating news could promote preferences alteration and make people overestimate background risk. It is well-known that present-oriented preferences could stymie the battery of economic growth. Therefore, the information about disasters should be delivered with caution.

6. Conclusion

This paper examines the effect of *Sewol* ferry disaster on time use of people residing in the treatment region. Right after the sinking, with one-week bandwidth, both regression discontinuity and difference-in-differences estimates suggested that the immediate impacts of the disaster were decrease in market work and home production, and increase in leisure terms. Increasing bandwidth up to 65 days from the disaster, we observed the evolution of time use.

Intriguingly, the progression of treatment effect, the effect of the disaster on those in and around *Ansan-si*, was stable after about a month. This investigation implies that the treatment effects on time use are contraction in home production and increase in leisure1.

The neighboring region of the treated region (*Tier2*) also showed stable evolution of increased market work, which fits the reversed pattern of decrease in home production among treated region (*Tier1*). This suggests that disaster caused interaction between the treated and its neighboring regions. The fact that demographic groups having weak bargaining power primarily provided labor after the sinking backs up such interaction. The treatment effect was heterogeneous depending on demographic subgroups: older cohorts decreased market work significantly while younger cohorts increased working time. This difference seems to come from the expected future benefit of career; those highly educated and in rich family increased leisure1 precipitously compared with their counterparts. This may suggest that they cope with the psychological shock by increasing leisure1 as they can afford the adjustment costs with ample resources. As was expected, *Tier3* (the neighboring region of *Tier2*) was not affected by the sinking, corroborating our choice of treatment group. The re-allocations of time use in treated region were concentrated in daytime, and night time is the least affected.

This paper makes several novel contributions to the literature. First and foremost, our results could shed light on possible mechanism behind macro consequences of disaster. For example, Cavallo et al. (2013) addressed that disasters stunt growth only temporarily. Given that those in the treatment region (*Tier1*) did not reduce their market work and the people in *Tier2* (the neighboring region of *Tier1*) increased market work, it is not surprising that disasters have only limited effect. This may partly explain how economic growth does not get affected in the long run even with the stunted human capital accumulation from the disaster. Second, this is the first study examining time re-allocations in the wake of disaster. With the increasing number of disasters and the reach of disaster as a result of advancing media and information technology, how individuals re-allocate their time in front of disaster is both intriguing and important. Notably, as people get indirectly influenced by the media, the fact that our estimates reflect only pure psychological trauma is noteworthy. Third, the increase in leisure may have some implications on the welfare effect of disaster. Observing that the socioeconomically privileged groups increased their leisure1 more substantially relative to their counterparts, the less privileged might disproportionately suffer from disasters. What if the privileged compensate psychological shock from the disaster by enjoying more leisure or meeting friends?

Then, our findings indicate that the less privileged may not be able to cope with psychological trauma from disaster as much as the privileged presumably due to resource constraint. Fourth, heavy media coverage with provoking expressions should be restrained to minimize the disaster's effect as the cues for fearful recollection may promote preferences alteration.

References

Abadie, Alberto, Alexis Diamond and Jens Hainmueller. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105 (490), 493-505.

Aguiar, Mark and Erik Hurst. (2007a). Measuring Trends in Leisure: The Allocation of Time over Five Decades. *Quarterly Journal of Economics,* 122 (3), 969–1006.

———. (2007b). Life-Cycle Prices and Production. *American Economic Review,* 97 (5), 1533–59.

Aguiar, Mark, Erik Hurst and Loukas Karabarbounis. (2012). Recent Development in the Economics of Time Use. *Annual Review of Economics,* 4, 373–97.

———. (2013). Time Use during the Great Recession. *American Economic Review,* 103 (5), 1664–96.

Beaud, Mickael and Marc Willinger. (2015). Are People Risk Vulnerable? *Management Science*, 61 (3), 624-636.

Becker, Gary S. (1965). A Theory of the Allocation of Time. *Economic Journal*, 75 (299), 493–517.

Becker, Gary S. and Casey B. Mulligan. (1997). The Endogenous Determination of Time Preference. *Quarterly Journal of Economics*, 112 (3), 729-758.

Berlemann, Michael, Max Steinhardt and Jascha Tutt. (2015). Do Natural Disasters Stimulate Individual Saving? Evidence from a Natural Experiment in a Highly Developed Country. IZA Discussion Paper No. 9026.

Berlemann, Michael and Daniela Wenzel. (2015). Long-term Growth Effects of Natural Disasters: Empirical Evidence for Droughts. CESifo Working Paper No. 5598.

Blattman, Christopher and Edward Miguel. (2010). Civil War. *Journal of Economic Literature*, 48 (1), 3-57.

Callen, Michael, Isaqzadeh Mohammad, Long James D. and Sprenger Charles. (2014). Violence and Risk Preference: Experimental Evidence from Afghanistan. *American Economic Review*, 104 (1), 123–48.

Callen, Michael. (2015). Catastrophes and Time Preference: Evidence from the Indian Ocean Earthquake. *Journal of Economic Behavior & Organization*, 118, 199–214.

Cameron, Lisa and Manisha Shah. (2015). Risk-Taking Behavior in the Wake of Natural Disasters. *Journal of Human Resources,* 50 (2), 484-515.

Caruso, Germán and Sebastian Miller. (2015). Long Run Effects and Intergenerational Transmission of Natural Disasters: A Case Study on the 1970 Ancash Earthquake. *Journal of Development Economics,* 117, 134-150.

Cassar, Alessandra, Andrew Healy and Carl von Kessler. (2011). Trust, Risk, and Time Preference after a Natural Disaster: Experimental Evidence from Thailand. University of San Francisco Working Paper.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy and Juan Pantano. (2013). Catastrophic Natural Disasters and Economic Growth. *Review of Economics and Statistics, 95 (5), 1549-1561.*

Currie, Janet and Maya Rossin-Slater. (2013). Weathering the Storm: Hurricanes and Birth Outcomes. *Journal of Health Economics, 32, 487-503.*

Eckel, Catherine C., Mahmoud El-Gamal and Rick K. Wilson. (2009). Risk Loving After the Storm: A Bayesian-Network Study of Hurricane Katrina Evacuees. *Journal of Economic Behavior and Organization*, 69 (2), 110-124.

Gelman, Andrew and Guido Imbens. (2014). Why High-Order Polynomials Should Not Be Used in Regression

Discontinuity Designs. NBER Working Paper No. 20405.

Gelber, Alexander M. and Joshua W. Mitchell. (2012). Taxes and Time Allocation: Evidence from Single Women and Men. *Review of Economic* Studies, 79, 863-897.

Gollier, Christian and John W. Pratt. (1996). Risk Vulnerability and the Tempering Effect of Background Risk. *Econometrica*, 64 (5), 1109-1123.

Grimad, Franque and Sonia Laszlo. (2014). Long-Term Effects of Civil Conflict on Women's Health Outcomes in Peru. *World Development*, 54, 139-155.

Guler, Bulent and Temel Taskin. (2013). Does Unemployment Insurance Crowd Out Home Production? *European Economic Review*, 62, 1-16.

Hamermesh, Daniel S. (1999). Changing Inequality in Markets for Workplace Amenities. *Quarterly Journal of Economics*, 114 (4), 1085–1123.

———. (2002). Timing, Togetherness and Time Windfalls. *Journal of Population Economics*, 15 (4), 601–23.

Harris, Glenn W., John A. List and Charles Towe. (2007). Naturally Occurring Preferences and Exogenous Laboratory Experiments: A Case Study of Risk Aversion. *Econometrica*, 75 (2), 433–458.

Hong, Sok Chul, Dongyoung Kim and Etteum Lee. (2016). The Long-Term Human Toll of Natural Disasters: A Study of Fetal Exposure to the 1974 Super Tornado Outbreak. Working Paper.

Imas, Alex, Michael A. Kuhn and Vera Mironova. (2015). A History of Violence: Field Evidence on Trauma, Discounting and Present Bias. CESifo Working Paper No. 5338.

Ichino, Andrea and Rudolf Winter-Ebmer. (2004). The Long-Run Educational Cost of World War II. *Journal of Labor Economics*, 22 (1), 57-86.

IPCC. (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

Jacobsen, Joyce P. and Peter Kooreman. (2005). Timing Constraints and the Allocation of Time: The Effects of Changing Shopping Hours Regulations in the Netherlands. *European Economic Review*, 49 (1), 9-27.

Kim, Dongyoung and Young-Il Kim. (2016). Mental Health Cost of Terrorism: Study of the Charlie Hebdo Attack in Paris. Working Paper.

Kim, Young-Il and Jungmin Lee. (2014). The Long-Run Impact of a Traumatic Experience on Risk Aversion. *Journal of Economic Behavior & Organization*, 108, 174-186.

Krueger, Alan B. and Andreas Mueller. (2010). Job Search and Unemployment Insurance: New Evidence from Time Use Data. *Journal of Public Economics*, 94 (3–4), 298–307.

———. (2012). The Lot of the Unemployed: A Time Use Perspective. *Journal of European Economic Association*, 10 (4), 765–794.

Lee, Jungmin, Daiji Kawaguchi and Daniel S. Hamermesh. (2012). Aggregate Impacts of a Gift of Time. *American Economic Review*, 102 (3), 612–16.

León, Gianmarco. (2012). Civil Conflict and Human Capital Accumulation. *Journal of Human Resources*, 47 (4), 991–1022.

Lill, Felix. (2014, May 14). Wir sind die besten Helfer der Welt. *Neues Deutschland.* Retrieved from http://www.neues-deutschland.de/

Metcalfe, Robert, Nattavudh Powdthavee and Paul Dolan. (2011). Destruction and Distress: Using a Quasi-experiment to Show the Effects of the September 11 Attack on Subjective Well-being in the UK. *Economic Journal*, 121, F81-F103

Quiggin, John. (2003). Background Risk in Generalized Expected Utility Theory. *Economic Theory*, 22 (3), 607–611.

Ramey, Valerie A. and Neville Francis. (2009). A Century of Work and Leisure. *American Economic Journal: Macroeconomics*, 1 (2), 189–224.

Rehdanz, Katrin, Heinz Welsch, Daiju Narita and Toshihiro Okubo. (2015). Well-being Effects of a Major Natural Disaster: The Case of Fukushima. *Journal of Economic Behavior & Organization*, 116, 500-517.

Reynaud, Arnaud and Cecile Aubert. (2014). Do Natural Disasters Modify Risk Preferences? Evidence from a Field Experiment in Vietnam. Working Paper.

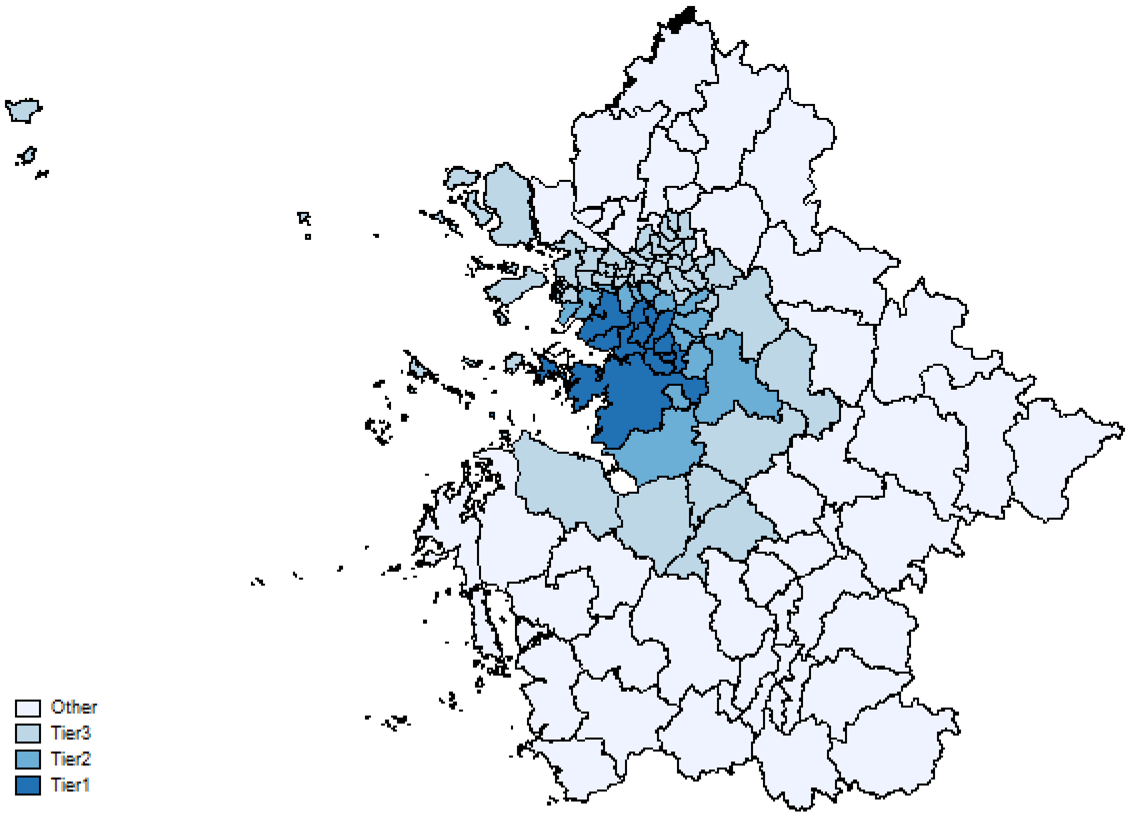
Skidmore, Mark and Hideki Toya. (2002). Do Natural Disasters Promote Long-run Growth? *Economic Inquiry*, 40 (4), 664-687.

Strobl, Eric. (2011). The Economic Growth Impact of Hurricanes: Evidence From U.S. Coastal Counties. *Review of Economics and Statistics*, 93 (2), 575-589.

The Heritage Foundation. (2016). Solutions 2016. Washington D.C.: The Heritage Foundation.

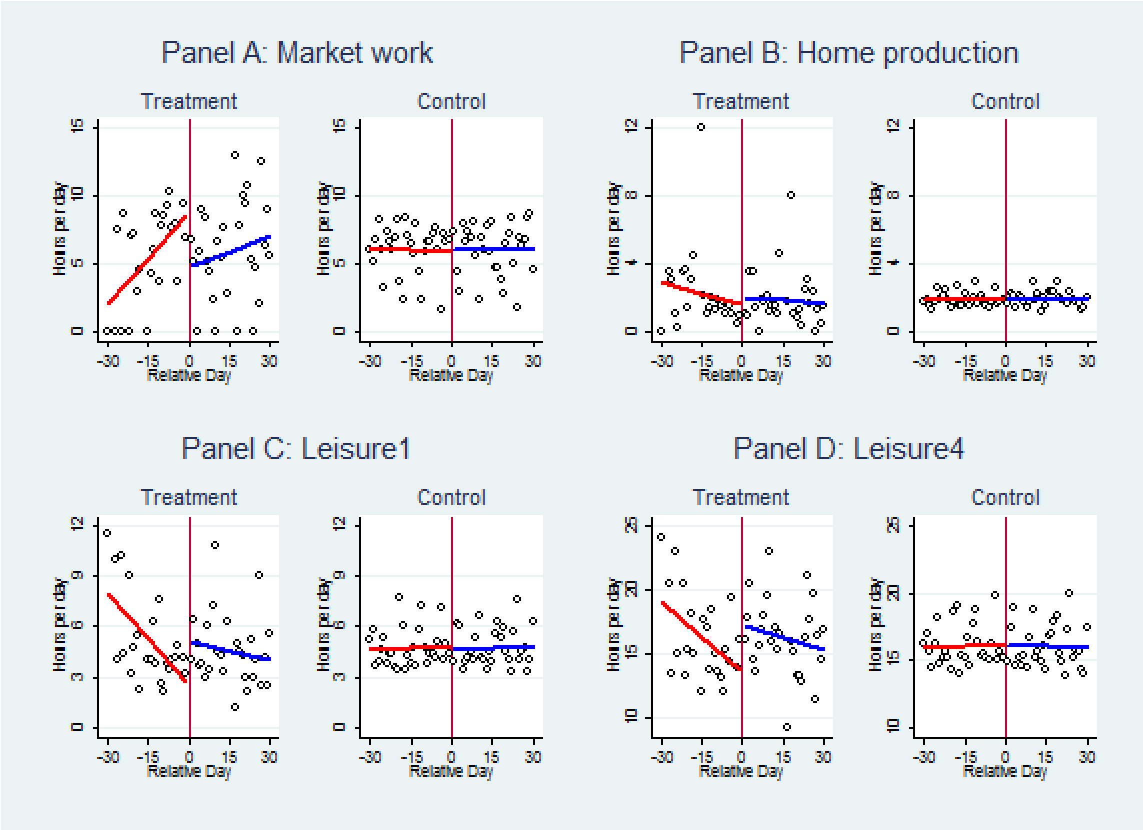
Voors, Maarten J., Eleonora E. M. Nillesen, Philip Verwimp, Erwin H. Bulte, Robert Lensink and Daan P. Van Soest. (2012). Violent Conflict and Behavior: A Field Experiment in Burundi. *American Economic Review*, 102 (2), 941–964.

[Figure 1] Map of Treatment Status – Tier1, Tier2, Tier3, and Other.



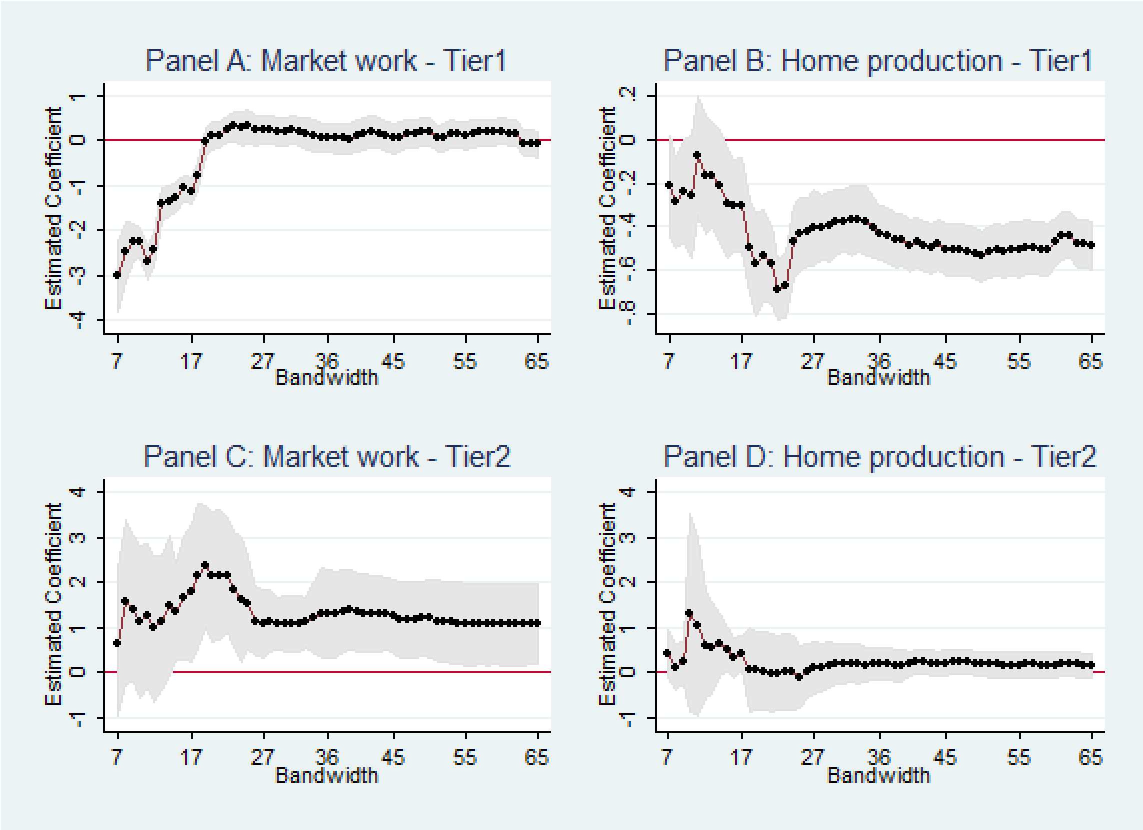
Note: We grouped South Korea into four categories. Depending on the geographic closeness to *Ansan-si*, we set *Ansan-si* and *si*-level counties around the it as Tier1, the neighboring counties of Tier1 as Tier2, and finally the adjacent *si*-level region of Tier2 as Tier3. Thus, Tier1, Tier2, and Tier3 are disjoint. The map shows only adjacent regions around our treatment groups.

[Figure 2] Time use of individuals pre- and post-Sewol sinking.



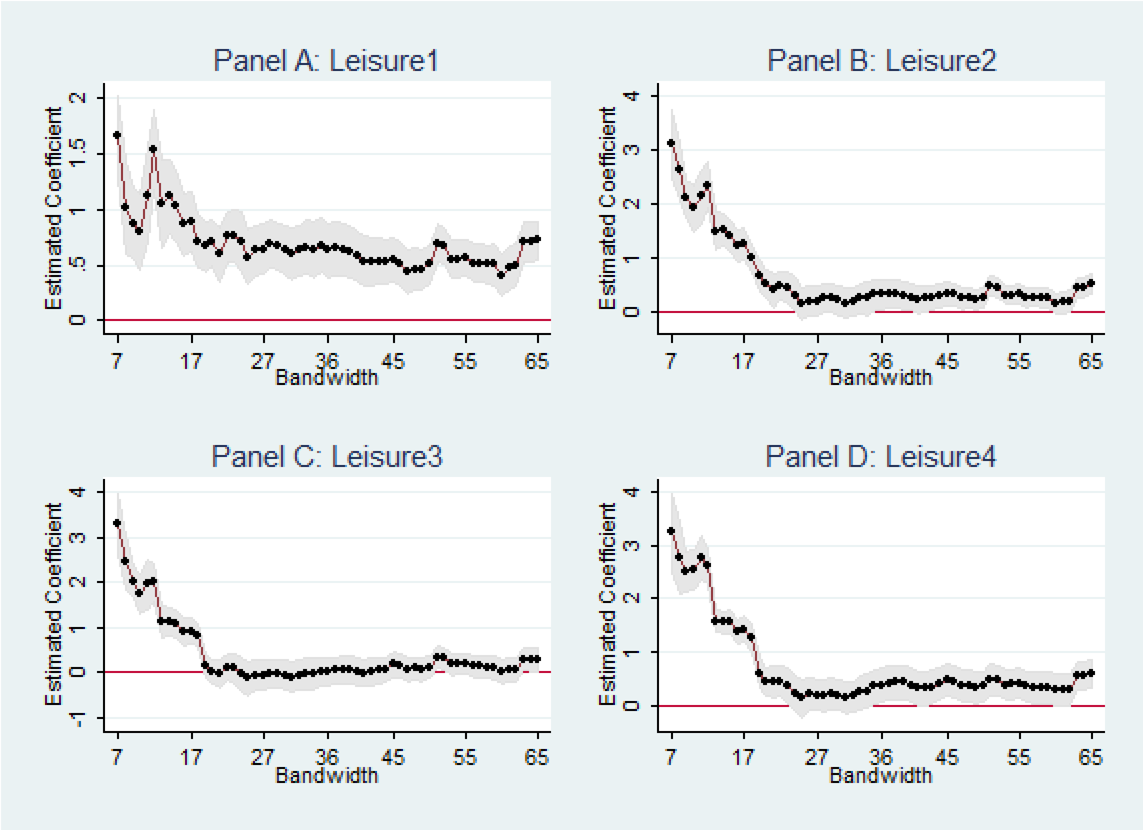
Note: Treatment indicates Tier1 and Control is the rest of Korea. The x-axis is the relative day from the sinking, where each day represents the time use reference date. The y-axis is the total amound of hours per day spent in the corresponding time use category. Linear polynomials are used to fit the data.

[Figure 3] Evolution of market work and home production – Tier1 and Tier2.



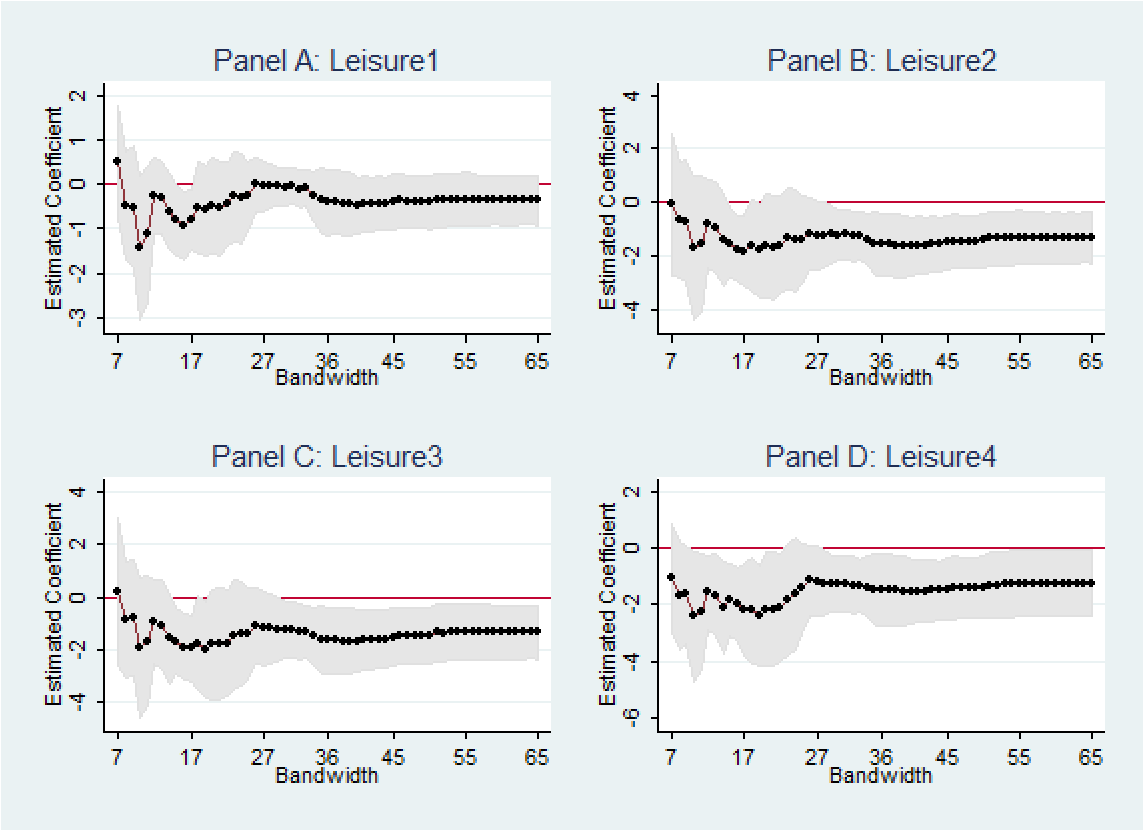
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier1_i$ and $Sewol_i \times Tier2_i$, against the choice of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure 4] Evolution of different measures of leisure – Tier1.



Note: We plotted the estiamted coefficients of $Sewol_i \times Tier1_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure 5] Evolution of market work and home production – Tier2.



Note: We plotted the estiamted coefficients of $Sewol_i \times Tier2_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

Table 1. Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Sewol Incident	Entire sample		O	O	X	X	DID
Treatment (Tier1)	Mean	Std. Dev.	O	X	O	X	p-value
Dependent Variables							
Market work	6.43	5.19	5.71	6.34	7.50	6.51	0.171
Home production	1.75	2.32	1.68	1.85	1.10	1.69	0.530
Leisure1	4.61	3.42	4.97	4.57	3.87	4.67	0.465
Leisure2	14.59	3.94	15.36	14.51	13.52	14.68	0.214
Leisure3	15.28	4.15	16.13	15.32	14.65	15.23	0.133
Leisure4	15.82	4.37	16.61	15.81	15.40	15.80	0.229
Covariates							
Male	0.48	0.50	0.56	0.48	0.52	0.47	0.855
Age	41.78	10.27	41.64	41.49	40.19	42.18	0.718
Education - Junior high or below (compulsory)	0.15	0.36	0.06	0.12	0.06	0.19	0.325
Education - Senior high	0.43	0.50	0.64	0.42	0.45	0.43	0.331
Education - College or above	0.42	0.49	0.31	0.46	0.48	0.38	0.194
Single	0.27	0.44	0.36	0.26	0.29	0.28	0.751
Self-reported health	2.42	0.67	2.36	2.37	2.19	2.50	0.051
Not employed	0.26	0.44	0.25	0.27	0.23	0.26	0.446
Number of family members	3.33	1.11	3.00	3.35	3.35	3.34	0.019
Log of adjusted family income	9.13	0.87	8.65	9.17	9.37	9.11	0.000
Number of children under age five	0.19	0.40	0.19	0.22	0.32	0.16	0.895
Number of children under age twenty	0.47	0.50	0.44	0.46	0.45	0.48	0.407
Sample size	1,044		36	485	31	492	

Note: Sample weight reported in KLIPS is used for calculating p-value in column (7).

Table 2. Effects of Exposure to the Sewol Disaster on Time Use

Key control	Market work	Home production	Leisure1	Leisure2	Leisure3	Leisure4
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Controlling for district fixed effect within Tier1						
Sewol	-0.1536	0.1374	-0.1233	-0.2600	0.0164	0.0162
	(0.3806)	(0.1740)	(0.3223)	(0.4387)	(0.4000)	(0.3995)
Sewol × Tier1	-3.3104***	-0.1003	1.9328***	3.2399***	2.7235***	3.4107***
	(0.3806)	(0.1740)	(0.3223)	(0.4387)	(0.4000)	(0.3995)
Tier1	1.6818***	-0.7603***	-0.8646***	-0.5282***	-0.8565***	-0.9216***
	(0.1996)	(0.1566)	(0.1252)	(0.1228)	(0.1347)	(0.2029)
R-squared	0.009	0.010	0.007	0.010	0.006	0.013
Panel B: Controlling for personal variables and day of the week effects						
Sewol	-0.0725	0.1627	-0.0100	-0.1208	0.0435	-0.0902
	(0.1904)	(0.1319)	(0.2026)	(0.2274)	(0.1986)	(0.2619)
Sewol × Tier1	-2.9002***	0.0178	1.2347***	2.4455***	2.6093***	2.8824***
	(0.2938)	(0.1638)	(0.2859)	(0.3267)	(0.3392)	(0.3519)
Tier1	-0.2690	0.0940	-0.1815	0.2668	0.5581	0.1750
	(0.3441)	(0.0932)	(0.4044)	(0.3888)	(0.4299)	(0.3708)
R-squared	0.613	0.499	0.332	0.362	0.361	0.535
Panel C: Controlling for province fixed effects						
Sewol	-0.1154	0.1789	-0.0125	-0.1403	0.0227	-0.0635
	(0.2131)	(0.1333)	(0.1901)	(0.2190)	(0.2112)	(0.2874)
Sewol × Tier1	-2.8692***	0.0454	1.2047***	2.4620***	2.6274***	2.8238***
	(0.3094)	(0.1755)	(0.2702)	(0.3277)	(0.3491)	(0.3975)
Tier1	-0.5345**	0.1378	0.2160	0.9801**	1.2301***	0.3967
	(0.2054)	(0.1643)	(0.3345)	(0.3500)	(0.3560)	(0.2415)
R-squared	0.618	0.530	0.350	0.376	0.372	0.541
Panel D: Controlling for county fixed effects - Baseline model						
Sewol	-0.0892	0.2761*	-0.2089	-0.4333*	-0.2157	-0.1869
	(0.2197)	(0.1438)	(0.1916)	(0.2446)	(0.1950)	(0.2153)
Sewol × Tier1	-3.0649***	-0.2396*	1.6287***	3.0944***	3.2948***	3.3045***
	(0.3843)	(0.1140)	(0.1948)	(0.2864)	(0.3260)	(0.3608)
R-squared	0.680	0.624	0.468	0.472	0.475	0.626
Panel E: Regression Discontinuity Design						
Sewol	1.2196*	0.4264	-0.6130	-1.2445*	-0.9136	-1.6461**
	(0.6878)	(0.4791)	(0.7767)	(0.6778)	(0.7140)	(0.6136)
Sewol × Tier1	-3.1796***	-0.2497*	1.6756***	3.1743***	3.3719***	3.4292***
	(0.3973)	(0.1319)	(0.2159)	(0.2805)	(0.3332)	(0.3586)
R-squared	0.681	0.624	0.469	0.474	0.477	0.628
Sample size	1,044	1,044	1,044	1,044	1,044	1,044

Note : Sample weight reported in KLIPS is used as regression weight. The standard errors of regression coefficients, reported in parentheses, are clustered on province. A single asterisk denotes statistical significance at the 90% level of confidence, double 95%, and triple 99%.

Table 3. Subgroup Analysis

Key control	Market work		Home production		Leisure1		Leisure2		Leisure3		Leisure4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sewol ×	Tier1	Tier2	Tier1	Tier2	Tier1	Tier2	Tier1	Tier2	Tier1	Tier2	Tier1	Tier2
Panel A: Age												
a. Forty or above	-0.6475***	1.4596**	-0.1886*	-0.1125	0.6817***	-0.4428	0.6727***	-1.3322**	0.8458***	-1.3743**	0.8361***	-1.3470*
	(0.1347)	(0.6781)	(0.0987)	(0.1351)	(0.1177)	(0.5480)	(0.1117)	(0.5521)	(0.1183)	(0.6412)	(0.1526)	(0.7397)
b. Below forty	0.3975*	0.4624	-0.6247***	0.6040*	1.1554***	0.0200	0.9022***	-0.9984	0.1053	-1.0942	0.2273	-1.0664*
	(0.2172)	(0.3770)	(0.1109)	(0.3248)	(0.1825)	(0.3260)	(0.1817)	(0.7404)	(0.2478)	(0.7060)	(0.2441)	(0.5946)
Sample mean (a/b)	6.99/5.77		2.01/1.52		4.64/4.51		14.49/14.50		14.77/15.67		15.03/16.71	
Sample size (a/b)	3,780/2,731		3,780/2,731		3,780/2,731		3,780/2,731		3,780/2,731		3,780/2,731	
Panel B: Education												
a. College or above	-0.8047***	0.5273*	-0.8063***	0.0999	1.1069***	0.0867	1.6082***	-0.7221	1.3078***	-0.5338	1.6110***	-0.6273**
	(0.2261)	(0.2511)	(0.1284)	(0.2246)	(0.1632)	(0.2225)	(0.2078)	(0.5157)	(0.2261)	(0.5624)	(0.1810)	(0.2943)
b. Below college	0.3942**	1.3137*	-0.2917***	0.1226	0.6075***	-0.4276	-0.1645	-1.4290	-0.3099*	-1.6340	-0.1025	-1.4363
	(0.1750)	(0.7455)	(0.0932)	(0.3301)	(0.1213)	(0.7682)	(0.1807)	(1.1470)	(0.1741)	(1.0868)	(0.1802)	(1.0200)
Sample mean (a/b)	6.68/6.30		1.63/1.94		4.28/4.82		14.22/14.70		15.20/15.11		15.69/15.77	
Sample size (a/b)	2,787/3,724		2,787/3,724		2,787/3,724		2,787/3,724		2,787/3,724		2,787/3,724	
Panel C: Log family income												
a. Median or above	-0.1937	1.4120	-0.7070***	0.1986	0.8736***	-0.8508*	1.0568***	-1.9524**	0.9978***	-1.7437*	0.9006***	-1.6106
	(0.2590)	(0.8214)	(0.1336)	(0.3160)	(0.2205)	(0.4182)	(0.2428)	(0.7601)	(0.2387)	(0.9433)	(0.2504)	(1.1159)
b. Below median	0.3757	0.9334*	-0.3105***	0.1231	0.1666	0.1387	-0.4223	-0.8281*	-0.7470**	-1.0117*	-0.0652	-1.0565**
	(0.3116)	(0.4568)	(0.0620)	(0.0857)	(0.2000)	(0.1706)	(0.2558)	(0.4202)	(0.3210)	(0.5625)	(0.2668)	(0.3912)
Sample mean (a/b)	6.57/6.35		1.71/1.90		4.64/4.54		14.47/14.52		14.97/15.32		15.73/15.75	
Sample size (a/b)	3,255/3,256		3,255/3,256		3,255/3,256		3,255/3,256		3,255/3,256		3,255/3,256	

Note : Sample weight reported in KLIPS is used as regression weight. The standard errors of regression coefficients, reported in parentheses, are clustered on province. A single asterisk denotes statistical significance at the 90% level of confidence, double 95%, and triple 99%.

Table 4. The Timing of Re-Allocation

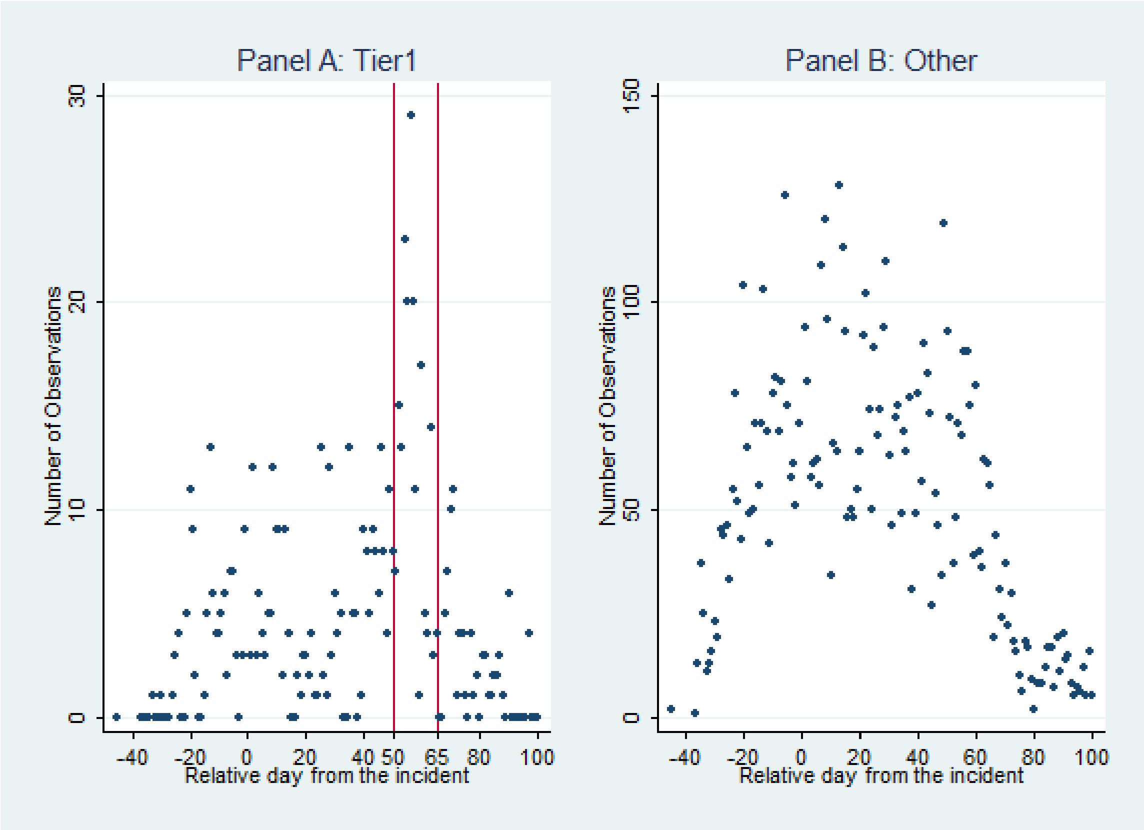
Key control	Market work	Home production	Leisure1	Leisure2	Leisure3	Leisure4
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Morning (6:00~12:00)						
Sewol	-0.0294	0.0806**	0.0066	-0.0412	-0.0538	-0.0512
	(0.0694)	(0.0341)	(0.0281)	(0.0562)	(0.0634)	(0.0780)
Sewol × Tier1	0.2000**	-0.1930***	0.1956***	-0.0443	-0.1134	-0.0070
	(0.0848)	(0.0432)	(0.0336)	(0.0691)	(0.0762)	(0.0858)
Sewol × Tier2	0.4664**	-0.0711	-0.1628**	-0.4211**	-0.3754**	-0.3953**
	(0.1851)	(0.0415)	(0.0567)	(0.1545)	(0.1634)	(0.1739)
R-squared	0.528	0.457	0.284	0.284	0.294	0.433
Panel B: Daytime (12:00~19:00)						
Sewol	-0.0784	-0.0007	0.1179*	0.1237	0.0903	0.0791
	(0.0628)	(0.0443)	(0.0635)	(0.0759)	(0.0797)	(0.0754)
Sewol × Tier1	-0.0638	-0.1967***	0.3275***	0.4257***	0.2951***	0.2605***
	(0.0721)	(0.0398)	(0.0553)	(0.0661)	(0.0760)	(0.0810)
Sewol × Tier2	0.5318**	0.0011	-0.2399	-0.5769***	-0.6200***	-0.5329***
	(0.2072)	(0.1066)	(0.1495)	(0.1457)	(0.1484)	(0.1709)
R-squared	0.586	0.343	0.361	0.366	0.378	0.521
Panel C: Evening (19:00~22:00)						
Sewol	-0.0896**	0.0695***	0.0162	0.0118	0.0163	0.0201
	(0.0339)	(0.0175)	(0.0523)	(0.0523)	(0.0504)	(0.0390)
Sewol × Tier1	-0.2058***	-0.0867***	0.0786	0.2166***	0.2236***	0.2926***
	(0.0402)	(0.0239)	(0.0516)	(0.0491)	(0.0456)	(0.0394)
Sewol × Tier2	0.1087	0.1344	-0.1975*	-0.2562*	-0.2801*	-0.2431
	(0.0966)	(0.1362)	(0.1037)	(0.1324)	(0.1400)	(0.1794)
R-squared	0.174	0.216	0.181	0.182	0.153	0.193
Panel D: Night (22:00~6:00)						
Sewol	-0.0874**	-0.0013	0.0427	0.1039*	0.0993*	0.0887**
	(0.0377)	(0.0147)	(0.0387)	(0.0489)	(0.0494)	(0.0379)
Sewol × Tier1	-0.0175	-0.0123	0.1233**	-0.1057*	-0.1119*	0.0298
	(0.0461)	(0.0161)	(0.0443)	(0.0560)	(0.0578)	(0.0488)
Sewol × Tier2	-0.0367	0.0894	0.2282	-0.0767	-0.0591	-0.0527
	(0.1253)	(0.0660)	(0.1633)	(0.1546)	(0.1469)	(0.1581)
R-squared	0.103	0.123	0.213	0.092	0.090	0.101
Sample size	6,511	6,511	6,511	6,511	6,511	6,511

Note : Sample weight reported in KLIPS is used as regression weight. The standard errors of regression coefficients, reported in parentheses, are clustered on province. A single asterisk denotes statistical significance at the 90% level of confidence, double 95%, and triple 99%.

NOT FOR PUBLICATION

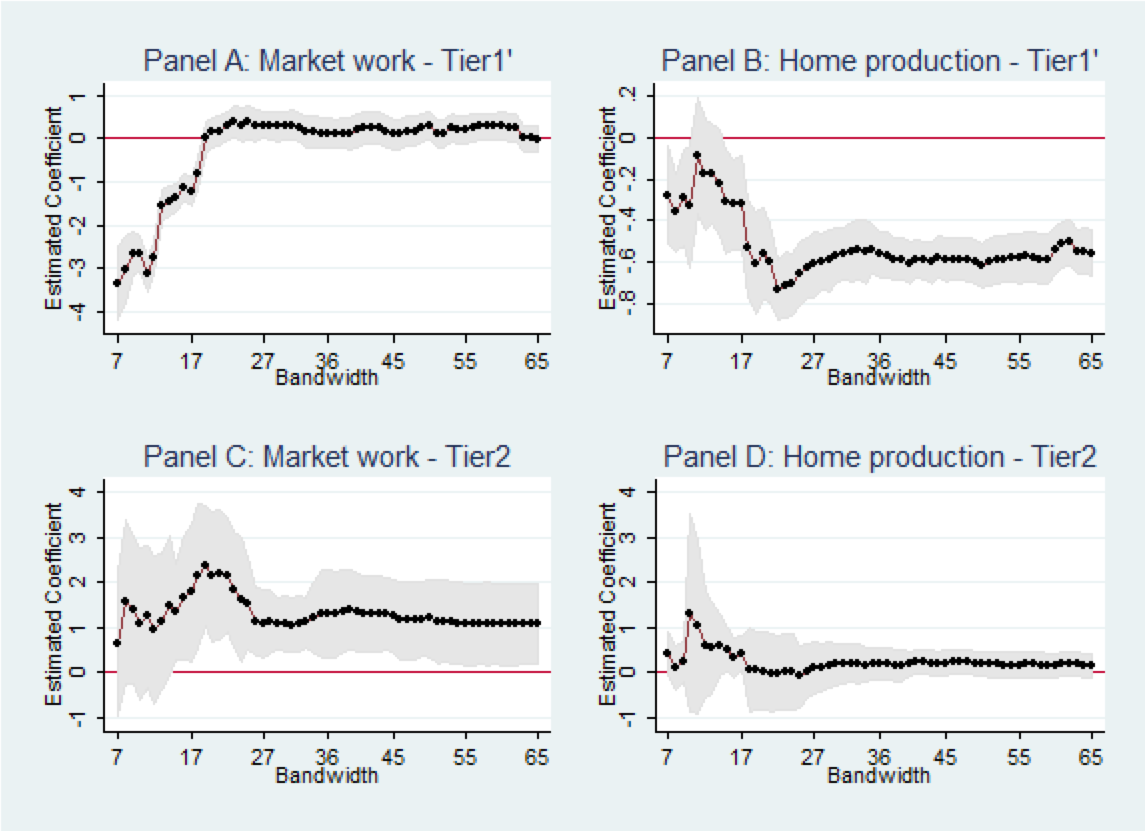
(Online Appendix)

[Figure A1] Number of observations per time use reference date – Tier1 and Other.



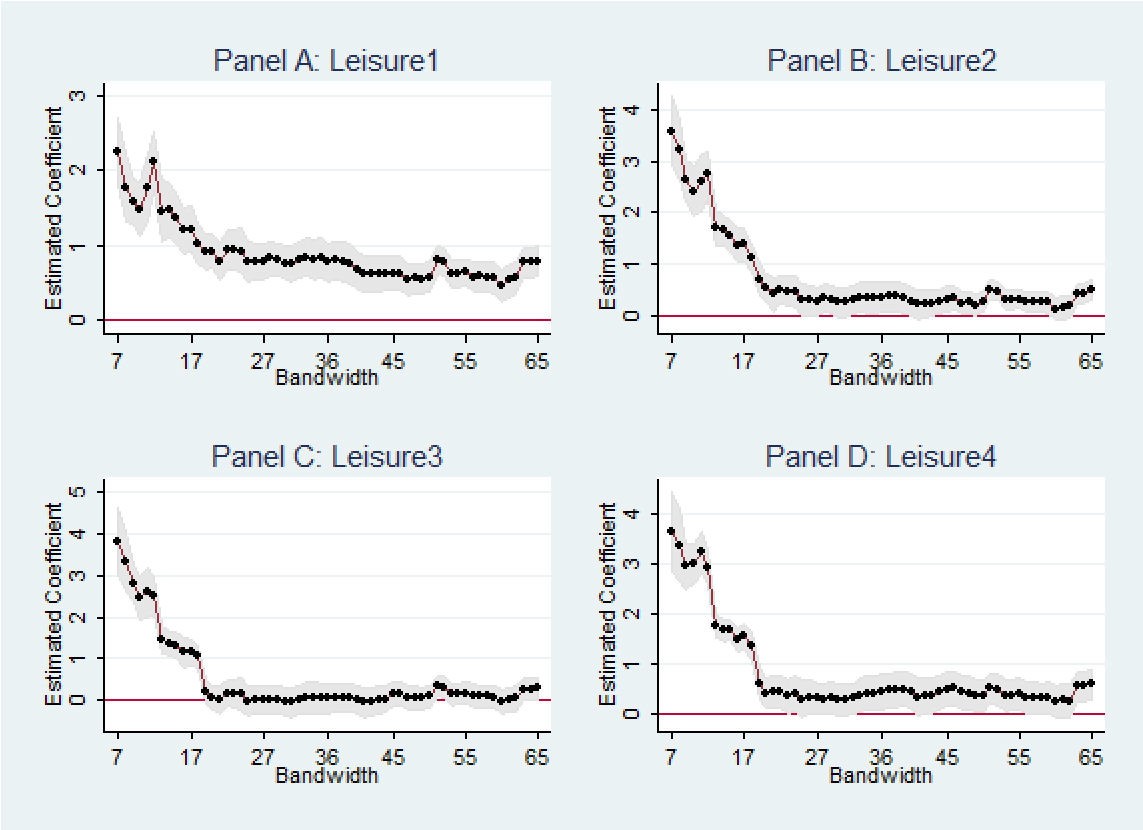
Note: We plotted the number of respondents in each time use reference date for Tier1 and Other, respectively. Relative day from the sinking indicates days passed after the disaster. For example, the day right before the sinking has the value of -1, the day right after the sinking has the value of 1, and so on.

[Figure A2] Evolution of market work and home production – Tier1' and Tier2.



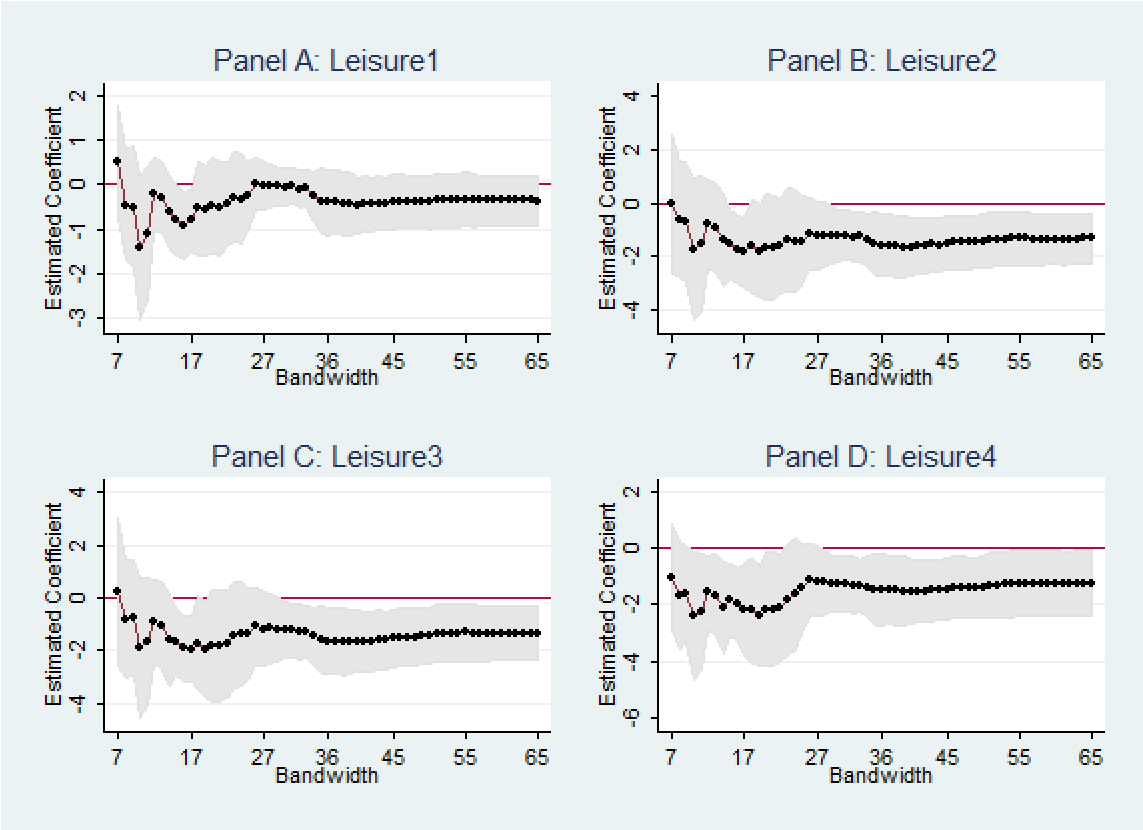
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier1'_i$ and $Sewol_i \times Tier2_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure A3] Evolution of different measures of leisure – Tier1'.



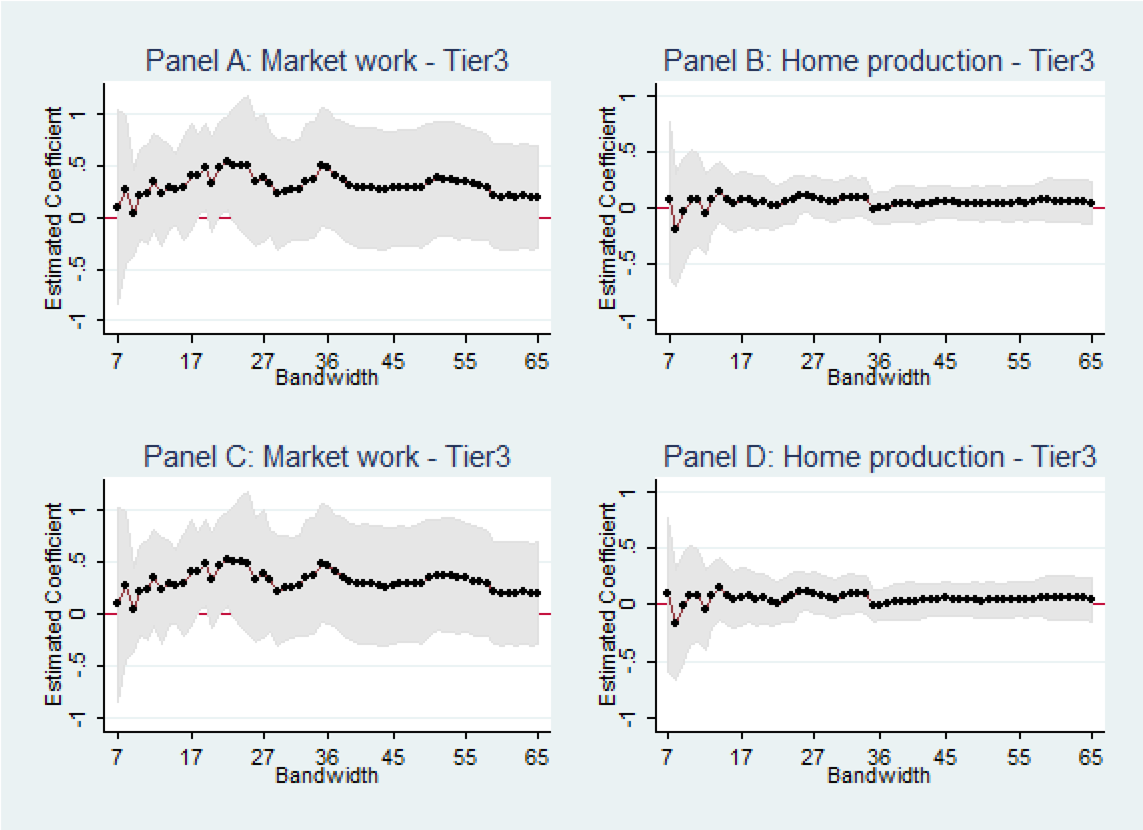
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier1'_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure A4] Evolution of different measures of leisure – Tier2.



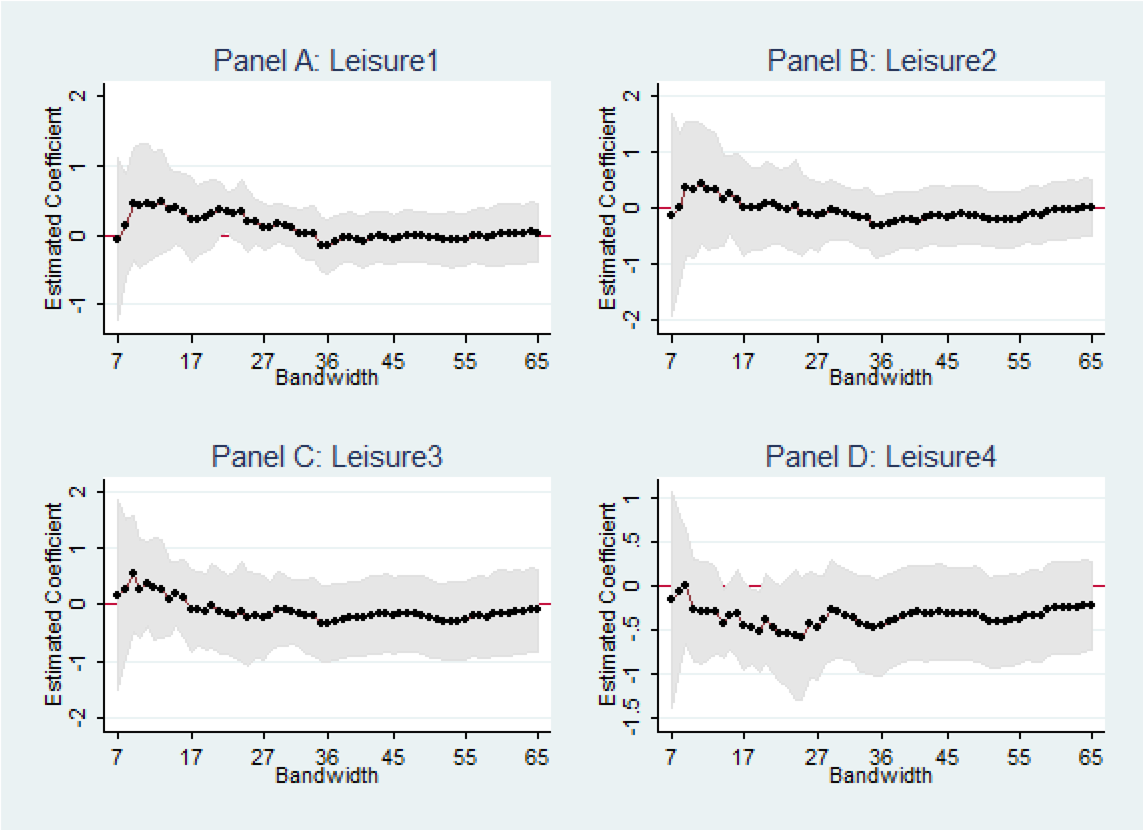
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier2_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure A5] Evolution of market work and home production – Tier3.



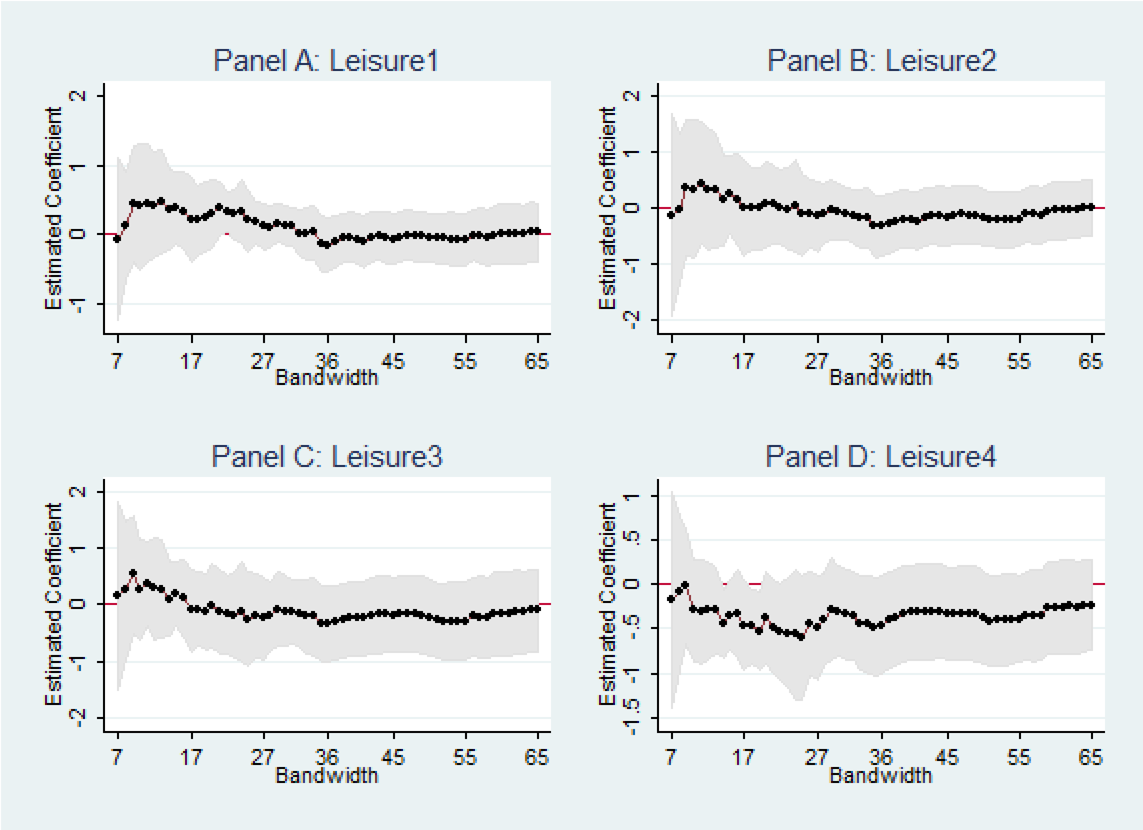
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier3_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure A6] Evolution of different measures of leisure – Tier3.



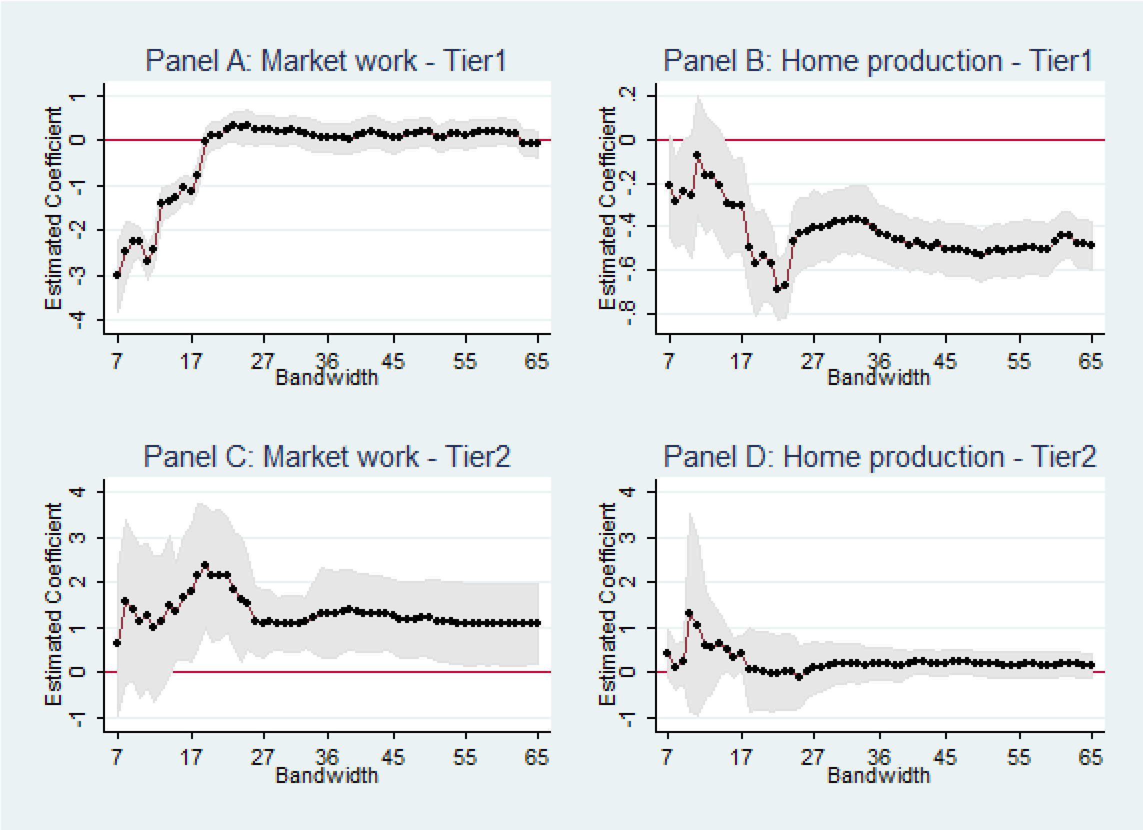
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier3_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure A7] Evolution of different measures of leisure – Tier3.



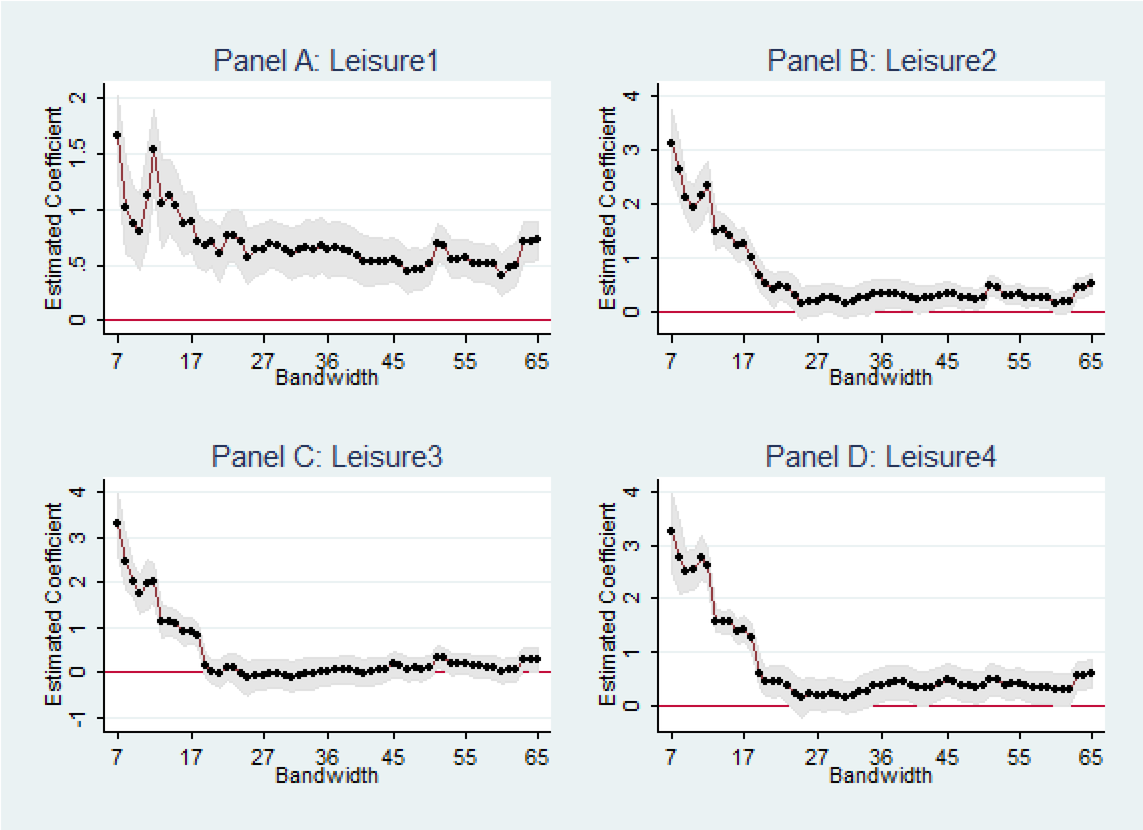
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier3_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient.

[Figure A8] Evolution of market work and home production – Tier1 and Tier2 (excluding southern coast).



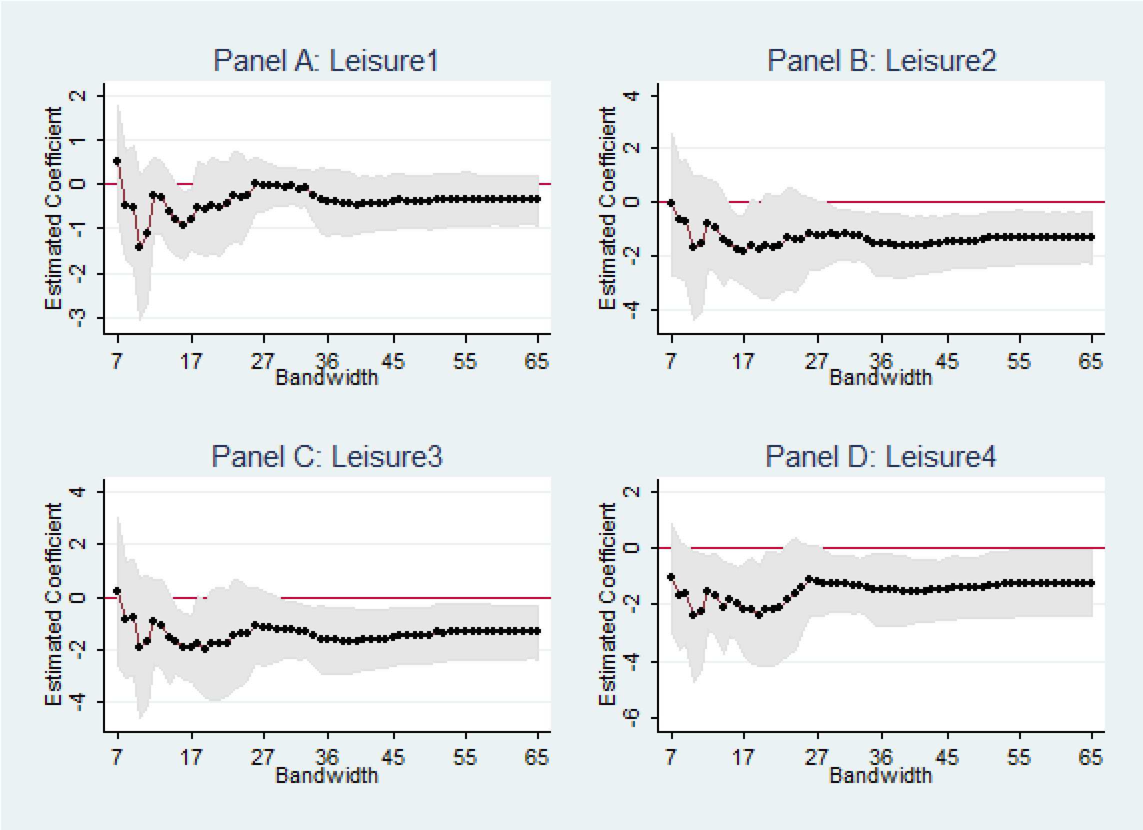
Note: We plotted the estiamted coefficients of $Sewol_i \times Tier1_i$ and $Sewol_i \times Tier2_i$ against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient. The analyses are conducted by excluding the sample living in southern coast, where the ferry sank.

[Figure A9] Evolution of different measures of leisure – Tier1 (excluding southern coast).



Note: We plotted the estiamted coefficients of $Sewol_i \times Tier1_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient. The analyses are conducted by excluding the sample living in southern coast, where the ferry sank.

[Figure A10] Evolution of different measures of leisure – Tier2 (excluding southern coast).



Note: We plotted the estiamted coefficients of $Sewol_i \times Tier2_i$, against the selection of bandwidth. Shaded area represents 95% confidence interval of the corresponding coefficient. The analyses are conducted by excluding the sample living in southern coast, where the ferry sank.

Table A1. Effects of the Sewol Disaster on Time Use - Hyperbolic Distance

Key control	Market work	Home production	Leisure1	Leisure2	Leisure3	Leisure4
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No control						
Sewol	-0.1917	0.1897	-0.1572	-0.2800	-0.0167	0.0021
	(0.3785)	(0.1904)	(0.3086)	(0.4351)	(0.4038)	(0.4018)
Sewol × (1/Distance)	-2.4657*	-0.9083**	2.0423**	2.7545**	3.7697***	3.3740**
	(1.2070)	(0.3332)	(0.8572)	(1.2809)	(1.1860)	(1.3919)
(1/Distance)	1.2942**	0.6742**	-1.3517***	-1.8036***	-1.8208***	-1.9684***
	(0.5515)	(0.3147)	(0.2619)	(0.2984)	(0.3042)	(0.5801)
R-squared	0.001	0.002	0.001	0.002	0.002	0.001
Panel B: Controlling for personal variables and day of the week effects						
Sewol	-0.0723	0.2125	-0.0463	-0.1299	-0.0145	-0.1402
	(0.1755)	(0.1415)	(0.1988)	(0.2374)	(0.1972)	(0.2520)
Sewol × (1/Distance)	-1.9480***	-1.0579***	1.2149**	1.6183***	3.4311***	3.0059***
	(0.4329)	(0.2443)	(0.4400)	(0.5164)	(0.4357)	(0.5383)
(1/Distance)	1.4306***	0.5714	-0.7643	-0.8235	-2.2183***	-2.0020***
	(0.3845)	(0.3784)	(0.5404)	(0.7884)	(0.7398)	(0.4687)
R-squared	0.610	0.497	0.323	0.349	0.351	0.531
Panel C: Controlling for area fixed effects						
Sewol	-0.1181	0.2291	-0.0712	-0.1554	-0.0353	-0.1110
	(0.1909)	(0.1402)	(0.1856)	(0.2185)	(0.2007)	(0.2653)
Sewol × (1/Distance)	-1.8525***	-1.1836***	1.0450**	1.5674***	3.3664***	3.0361***
	(0.3854)	(0.1921)	(0.3865)	(0.4862)	(0.4295)	(0.4141)
(1/Distance)	0.8292***	0.6002**	0.4005	0.8242	-0.7736	-1.4294***
	(0.2496)	(0.2582)	(0.3469)	(0.5206)	(0.5083)	(0.4011)
R-squared	0.615	0.529	0.343	0.366	0.363	0.537
Panel D: Controlling for area fixed effects - distance						
Sewol	-0.3207	0.2393	0.0001	-0.2233	0.0468	0.0813
	(0.2674)	(0.2368)	(0.1343)	(0.1852)	(0.2586)	(0.3544)
Sewol × Distance	0.0011	-0.0004	-0.0004	0.0008	0.0001	-0.0007
	(0.0015)	(0.0012)	(0.0015)	(0.0018)	(0.0018)	(0.0016)
Distance	-0.0037	-0.0005	0.0142***	0.0159**	0.0141*	0.0041
	(0.0075)	(0.0026)	(0.0046)	(0.0073)	(0.0078)	(0.0073)
R-squared	0.615	0.529	0.347	0.369	0.364	0.537
Panel E: Regression Discontinuity Design						
Sewol	-0.0470	0.3634	-0.0242	-0.3048	0.0706	-0.3163
	(0.4528)	(0.3488)	(0.7192)	(0.6173)	(0.5223)	(0.5395)
Sewol × (1/Distance)	-1.6396***	-1.1645***	0.7410	1.1820**	2.8402***	2.8041***
	(0.3879)	(0.2095)	(0.4566)	(0.4097)	(0.3664)	(0.4040)
(1/Distance)	0.7213**	0.5902**	0.5540	1.0195*	-0.5080	-1.3115***
	(0.2622)	(0.2647)	(0.3547)	(0.4925)	(0.4780)	(0.4104)
R-squared	0.616	0.529	0.345	0.368	0.366	0.538
Sample size	1,044	1,044	1,044	1,044	1,044	1,044

Note : Sample weight reported in KLIPS is used as regression weight. The standard errors of regression coefficients, reported in parentheses, are clustered on province. A single asterisk denotes statistical significance at the 90% level of confidence, double 95%, and triple 99%.