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Rising waters, falling well-being: The effects of the 2013 East German flood on subjective well-being

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Abstract

This paper employs a panel event study design to examine the causal effects of the 2013 flood disaster in East Germany on subjective well-being. We merge geo-spatial flood data with longitudinal data from the German Socio-Economic Panel (SOEP) to identify individuals in affected municipalities. Our results show that those affected by the flood report a significant life satisfaction drop of 0.17 points on an 11-point scale, which is equivalent to a 2.5% fall from pre-flood levels, in the year after the flood. The effect is more severe in peripheral areas than in central areas, and for low-income individuals than for high-income individuals. However, the effect dissipates by 2015. Additionally, we observe a notable initial decrease in health satisfaction, followed by recovery, while financial satisfaction was largely unaffected.

Keywords: natural disasters, flood, quality of life, life satisfaction, health satisfaction, financial satisfaction

JEL Classification: I31, Q51, Q54

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1 Introduction

Floods stand out as one of the most prevalent and severe natural disasters, causing extensive damage to the lives and living conditions of people (Hu et al., 2018). According to the Emergency Event Database (EM-DAT), floods constituted 46% of all natural disasters in 2022, impacting approximately 57 million individuals and causing economic losses of 44.9 billion USD (CRED, 2023). In June 2013, a severe flooding event struck Germany, primarily affecting the eastern and southern regions.[1] Persistent heavy rains that began in mid-May, combined with high levels of soil moisture, triggered extensive and severe flooding in several parts of these regions (Merz et al., 2014; Thieken et al., 2016). Hydrologically, this event was the most severe flood to impact the country in at least the past six decades (Merz et al., 2014). The flood caused significant material losses, with the total estimated damages in East Germany amounting to 4.2 billion euros, which is considerably higher than the 1.5 billion euros in damages reported in West Germany (DKKV, 2013).[2]

While the economic and physical impacts of the 2013 flood have been extensively documented, understanding the adverse non-monetary effects on people's quality of life and overall living circumstances remains an underexplored area. Recent research has documented that natural disasters, including floods, result in not only economic losses but also considerable psychological stress and other non-tangible effects (Ahmadiaini & Ferreira, 2021; Fluhrer & Kraehnert, 2022; Jensen & Tiwari, 2021; Luechinger & Raschky, 2009; von Möllendorff & Hirschfeld, 2016). This paper seeks to fill this research gap on the adverse non-monetary effects of natural disasters by investigating the causal effects of the 2013 flood on subjective well-being (SWB) in East Germany.

[1] The flooding occurred in particular along the Danube and Elbe rivers, the upper catchments of the rivers Rhine and Weser, and along the Elbe tributaries Mulde and Saale (Merz et al., 2014; Thieken et al., 2016).

[2] Particularly, Saxony suffered the highest losses estimated at 1.9 billion euros, followed by Saxony-Anhalt with 1.8 billion euros. Additionally, infrastructure damage, particularly to federal assets like railways and motorways, further compounded the financial burden (Federal Ministry of Interior and Community (BMI), 2013).

By examining the effects on SWB, we aim to provide a complementary assessment of the effects of a natural disaster. The SWB approach is relevant for policy-making as it focuses on individual experiences and is directly associated with the needs of those affected. This perspective can facilitate effective responses to these needs, thereby enhancing the recovery of those affected (Jensen & Tiwari, 2021; Mahoney, 2023). Specifically, SWB data can be used to design targeted interventions to support population subgroups experiencing particular well-being losses due to a natural disaster. For instance, if SWB data reveal that individuals living in peripheral areas report a significantly sharper decline in health satisfaction compared to those in central areas, this information could prompt the development of services to help individuals in peripheral areas in coping with the effects of the flood. Such services may include mobile counseling and psychological support to address trauma and stress related to the disaster.

This paper employs a panel event study design to examine the trajectory and magnitude of the causal effects of experiencing the 2013 flood on SWB in East Germany, a heavily impacted region. We conduct a causal analysis by comparing individuals residing in flood-affected municipalities with those in unaffected areas, thus employing the latter group to construct a counterfactual outcome for our examination. To identify individuals who experienced the flood, we combine geo-spatial flood data provided by Osberghaus and Fugger (2022) with survey data obtained from the German Socio-Economic Panel (SOEP).

We contribute to the existing literature on the consequences of flood disasters in two ways. First, we examine the causal effects of the 2013 flood on SWB. In particular, we contribute novel knowledge on the long-term effects of the 2013 flood in East Germany, which have not been previously addressed in the existing literature. Second, our study investigates two potential mechanisms through which natural disasters may impact well-being: the health channel, which includes psychological effects, and the financial channel. By delving into these mechanisms, we offer a new perspective on how a disaster impacts people's lives and living conditions.

Our findings suggest that the 2013 flood has a significant detrimental effect on individuals' life satisfaction. Those who experienced the flood report a decline in life satisfaction of 0.17 points on an 11-point scale in the year following the event, equivalent to a decrease of 2.5% compared to their average pre-flood life satisfaction. However, this negative impact reduced over time, specifically in 2015 and 2016. The effect is more severe in peripheral areas than in central areas, and for low-income individuals than for high-income individuals. Additionally, our results indicate that the decline in health satisfaction played an important role in the link between the flood and life satisfaction. In the first year after the flood, individuals reported a decrease in health satisfaction of 0.13 points on an 11-point scale. However, we observed a swift recovery in health satisfaction from 2015 onwards. Notably, our findings did not reveal a decline in financial satisfaction with the household income as a direct consequence of experiencing the flood.

2 Literature

The empirical literature examining the impact of natural disasters on well-being spans a wide range of events and geographical contexts, such as forest fires in Europe (Kountouris & Remoundou, 2011), droughts in Australia (Carroll et al., 2009), earthquakes in Japan (Ohtake et al., 2016; Okuyama & Inaba, 2017), hurricanes and tornadoes in the USA (Ahmadiaini & Ferreira, 2021), the combined effect of the nuclear accident triggered by a tsunami and earthquake in Japan (Rehdanz et al., 2015), and an extreme winter event in Mongolia (Fluhrer & Kraehnert, 2022). A common approach in this literature is to use self-reported life satisfaction to capture a comprehensive assessment of an individual's overall quality of life. In the economics literature, this measure serves as a proxy for utility (Frey & Stutzer, 2002). In line with the specific focus of this research, this section summarizes the empirical literature examining flood impacts on SWB.

An existing strand of literature assesses the impact of flood events on individuals' well-being by administering primary cross-sectional surveys (Hudson, Pham, & Bubeck, 2019; Hudson &

Aerts, 2017; Lamond et al., 2015; Murata et al., 2023; Sekulova & Van den Bergh, 2016). Lamond et al. (2015) analyze data from a postal survey of households impacted by the 2007 flood in England. They conclude that experiencing a flood is associated with long-lasting mental health impacts. Similarly, Sekulova and Van den Bergh (2016) conducted 600 face-to-face interviews in Bulgaria, finding that experiencing a flood, significantly reduces life satisfaction. Hudson and Aerts (2017) and Hudson, Pham, and Bubeck (2019) conducted cross-sectional surveys in France and Vietnam, respectively, in regions at high risk of flooding. Both studies document a negative impact of flood experience on SWB. More recently, Murata et al. (2023) conducted an online questionnaire in 2022 in the Tochigi Prefecture in Japan, which was affected by floods in 2019. The study concludes that flood experience negatively impacts SWB by increasing anxiety about floods among participants. While cross-sectional surveys can reveal important relationships, they cannot track changes in individuals over time. Moreover, the inability to include individual fixed effects to control for unobservable time-invariant heterogeneity affecting life satisfaction may result in non-causal estimates.

The second strand of literature uses repeated cross-sectional data or panel data to investigate the impact of floods on SWB (Ahmadiaini & Ferreira, 2021; Avdeenko & Eryilmaz, 2021; Luechinger & Raschky, 2009; von Möllendorff & Hirschfeld, 2016). These studies generally link SWB data from secondary surveys with flood data to identify individuals affected by flooding events. Luechinger and Raschky (2009) use self-reported life satisfaction from Eurobarometer surveys combined with disaster data from the EM-DAT to assess the impact of floods on well-being in 16 European countries between 1973 and 1998. They find that, on average, a person living in a region affected by a flood disaster reports a decrease in life satisfaction of 0.035 points on a 4-point scale compared to the reference group. Similarly, Ahmadiaini and Ferreira (2021) examine the impact of 31 major disasters, including floods, on the life satisfaction of US residents from 2004 to 2010. Using data from the Behavioral Risk Factor Surveillance System Surveys

(BRFSS), they find a significant and negative impact on the life satisfaction of those affected in the last 6 months of 0.009 points on a 4-point scale. Both the Eurobarometer and BRFSS, from which data on life satisfaction is extracted, are repeated cross-sectional datasets. In both studies, individuals are classified as affected by a flood if a flood disaster occurred in the respondent's region of residence in the month(s) preceding the interview. Ahmadiaini and Ferreira (2021) vary the treatment indicator by the number of preceding months before the disaster to construct temporal effects of the disaster experience. They find that the effect attenuates over time.

The studies by von Möllendorff and Hirschfeld (2016) and Avdeenko and Eryilmaz (2021) use the German Socio-Economic Panel (SOEP), which is a panel dataset. The use of longitudinal datasets provides an advantage because changes in an individual's SWB as a consequence of experiencing a flood can be observed. von Möllendorff and Hirschfeld (2016) examine the impact of extreme weather events on life satisfaction in Germany from 2000 to 2011. They exploit regional variation in damage frequency induced by floods, storms, and hailstorms, and find that an increase in damages is associated with a decrease in life satisfaction of 0.020-0.027 on the 11-point life satisfaction scale. Avdeenko and Eryilmaz (2021) examine the impact on risk preferences of those affected by the 2013 flood in Germany and identify a reduction in life satisfaction as a driving mechanism for reducing individuals' willingness to take risks.

Our study contributes to the existing literature by improving our understanding of the causal effects of experiencing a flood on life satisfaction. By using longitudinal data, our approach differs from previous studies that have used primary surveys and repeated cross-sectional data, allowing us to control for individual unobserved time-invariant heterogeneity. We implement a panel event study approach, which captures the dynamic effect of the flood and sheds light on the lasting impact of such natural disasters on SWB. Our study expands existing research also by investigating health and financial satisfaction as potential mechanisms through which floods impact well-being.

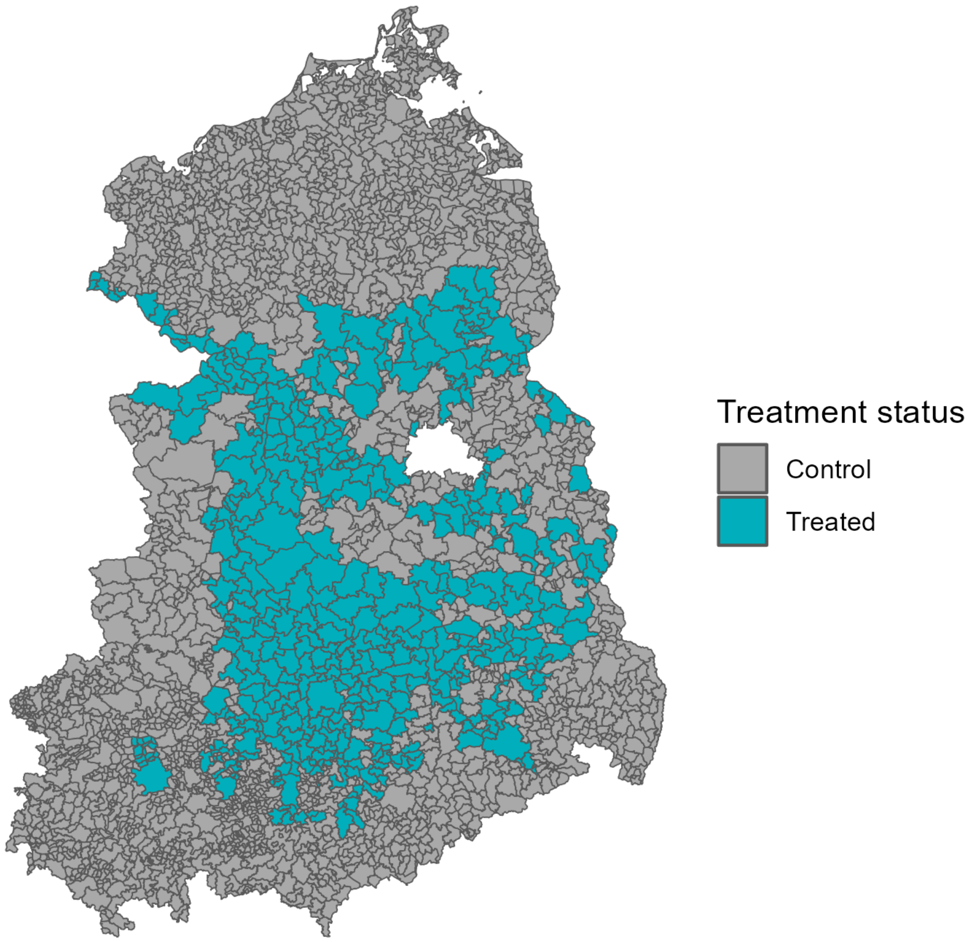
3 Data

We use data from two sources. The first source comes from Osberghaus and Fugger (2022) who utilize high-resolution satellite imagery to create a dataset detailing the small-scale geographic areas affected by the 2013 flood. The satellite imagery was sourced both from the German Aerospace Center (DLR) and NASA. The DLR data specifically include areas that experienced the highest impact from the flood, while the NASA data cover a wider range of areas, including areas with varying levels of impact. We use the dataset from Osberghaus and Fugger (2022) to classify municipalities in eastern Germany into two distinct groups: municipalities that experienced flooding and municipalities that were not affected. We classify a municipality as flooded if it has been identified in at least one of the two sources of satellite imagery. By doing so, we employ a finer geographical classification for treatment than used by previous studies. For instance, von Möllendorff and Hirschfeld (2016) conduct their analysis at the NUTS 3 level, Luechinger and Raschky (2009) use the NUTS 2 level, and Ahmadiaini and Ferreira (2021) perform their analysis at the US county level, all of which represent broader geographical classifications. Figure 1 shows a map of the treatment status of the municipalities.

The German Socio-Economic Panel (SOEP) serves as the second data source.[3] The SOEP offers comprehensive subjective and objective information on a wide range of topics (Goebel et al., 2019). Our main focus is on life satisfaction as a measure of SWB. In the SOEP survey, participants are asked: "How satisfied are you currently with your life in general?" The responses are recorded on an 11-point scale, ranging from 0 (completely dissatisfied) to 10 (completely satisfied). Additionally, we consider the participants' satisfaction with their health and their financial well-being as outcome variables. The corresponding survey questions specifically ask respondents to rate their satisfaction with health and household income, respectively. These variables are also measured on an 11-point scale.

[3] We use SOEPv38 samples A-K, Socio-Economic Panel (2023).

Figure 1: Treatment status: municipalities affected by the flood



Datasource: Osberghaus and Fugger, 2022

After merging the two datasets at the municipal level, we classify households into two categories: those that experienced the flood (treatment group) and those that did not (control group). To create a treatment group, we include respondents who resided in a flooded municipality in both 2013 and 2014. The control group consists of individuals who lived in unaffected municipalities during those years. Since we cannot unambiguously determine whether respondents who moved between a treated and a control municipality in these two years were affected by the flood or not, we exclude these individuals from the sample.

For the year 2013, we only consider information obtained before the occurrence of the flood. This allows us to classify all observations from 2013 as part of the pre-treatment period. As a result, any data collected after May 2013 is not included in our analysis. Our primary focus is on East Germany, as this region was heavily impacted by the flood. However, we exclude Berlin from our analysis as it was not affected by the flood and its size and structure make it unsuitable for comparison. This results in a sample size of 17,256 observations, of which 6,946 observations belong to the treatment group.[4]

Table 1: Covariate Balance in 2012

	Control		Treated		
Variable	Mean	S.D.	Mean	S.D.	Nor.Dif.
Married (0/1)	0.62	0.49	0.60	0.49	0.04
Single (0/1)	0.20	0.40	0.21	0.41	-0.04
Divorced (0/1)	0.10	0.30	0.10	0.30	-0.01
Widowed (0/1)	0.08	0.28	0.08	0.28	0.00
Disabled (0/1)	0.85	0.36	0.86	0.35	-0.02
Non-working (0/1)	0.40	0.49	0.42	0.49	-0.03
Unemployed (0/1)	0.07	0.25	0.07	0.25	0.00
Employed (0/1)	0.53	0.50	0.52	0.50	0.02
Education (in years)	12.26	2.32	12.71	2.64	-0.18
Female (0/1)	0.52	0.50	0.53	0.50	-0.00
Immigrant (0/1)	0.03	0.16	0.02	0.15	0.02
Age (in years)	53.65	16.79	54.45	16.64	-0.05
Monthly net hh-income	2,346	1,393	2,349	1,343	-0.00
Household size	2.40	1.13	2.24	0.96	0.16
Periphery (0/1)	0.77	0.42	0.38	0.49	0.84
Rural (0/1)	0.36	0.48	0.23	0.42	0.28
Life satisfaction	6.70	1.76	6.73	1.72	-0.02
Health satisfaction	6.21	2.22	6.21	2.17	-0.00
Financial satisfaction	5.90	2.32	6.12	2.24	-0.10

Note: Nor.Dif. is the normalized difference. Number of observations: control n=2,425; treated n=1,387.

Table 1 represents the sample means and standard deviations of the respondents' characteristics and outcomes by treatment group for the pre-flood year 2012. The column "Nor.Dif." shows

[4]In the case of the doubly robust difference-in-differences (DR DiD) estimator, the sample size is reduced to 15,653 observations, as the estimator requires observations in both the pre- and at least one post-period for each individual.

the normalized difference (Imbens & Rubin, 2015, Ch. 14.2), which is a scale-free measure of the difference in the covariate distributions between the two groups.[5]

When comparing the sample means of the treatment and control groups, it is evident that individuals affected and unaffected by the flood are generally similar, as indicated by values of the normalized difference that are below 0.1 (Nguyen et al., 2017). However, one noticeable difference between the treatment and control groups is apparent: a higher proportion of individuals living in peripheral areas are part of the control group compared to those living in central areas (77% vs. 38%).[6] Additionally, there are some modest differences regarding education and household size. Individuals in the treatment group have a slightly higher level of education (12.71 vs. 12.26) and reside in slightly smaller households (2.24 vs. 2.40).

4 Estimation strategy

We employ a panel event study design to estimate the trajectory of the effect of the 2013 flood. The outcome y_{imt} of individual i residing in municipality m at time t is modeled as follows:

$$y_{imt} = \mu_{2012} D_{mt,2012} + \sum_{\tau=2014}^{2016} \delta_\tau D_{mt,\tau} + \lambda_t + \alpha_i + \varepsilon_{imt} \tag{1}$$

$D_{mt,2012}$ and $D_{mt,\tau}$ are lead and lag indicators for the 2013 flood, respectively. The parameter μ_{2012} represents the lead effect of experiencing the 2013 flood. Its coefficient allows us to assess the plausibility of the parallel trends assumption that requires that outcomes in affected municipalities and unaffected municipalities would have evolved similarly in the absence of the flood. An estimate of μ_{2012} that is small and near zero suggests that affected and unaffected municipalities follow similar trends in the pre-treatment period, lending credibility to the parallel trends

[5]The normalized difference is defined as $\frac{\bar{x}_T - \bar{x}_C}{\sqrt{(s_T^2 + s_C^2)/2}}$, where $\bar{x}_T$, $\bar{x}_C$ correspond to the sample means of the covariates for the treatment and control group and s_T^2, s_C^2 to their sample variances, respectively.

[6]The classification into peripheral and central areas is based on the *Raumtypen 2010* typology of spatial location of the Federal Office for Building and Regional Planning (BBSR) (n.d.). We dichotomize the original 4-point scale into periphery (very peripheral, peripheral) and central (central, very central).

assumption. δ_τ represent the lag effects of experiencing the 2013 flood, allowing us to assess the evolution of the outcome. In particular, the lag effects may be indicative of whether the outcome returns to the pre-event level after some time. The model further includes year effects, λ_t, and individual fixed effects, α_i. ε_{imt} represents an idiosyncratic error term.

Equation 1 is estimated separately for our three measures of SWB using linear models. This implies an assumption of cardinality of SWB, which is generally supported by findings in the literature (e.g., Ferrer-i-Carbonell & Frijters, 2004). We estimate regressions with and without covariates. The model with covariates includes education, household size, marital status, settlement structure (differentiating between urban and rural), and geographical location (differentiating between periphery and central areas).

We additionally apply a doubly robust difference-in-differences (DR DiD) estimator as proposed by Sant'Anna and Zhao (2020), estimating a treatment assignment model and an outcome model. The DR DiD estimator provides consistent estimates if either the outcome or the treatment assignment model is correctly specified. The DR DiD estimation is based on the following pre-treatment covariates: education, gender, immigrant status, age, employment status, household income, household size, settlement structure, geographical location, and the respective pre-treatment outcome variable.

We employ a cluster-robust variance-covariance estimator in our study to calculate standard errors that are clustered at the municipality level, thereby accounting for correlations within each municipality. In doing so, we address concerns about within-cluster correlation that may arise as we follow outcomes of respondents over time within municipalities (Bertrand et al., 2004; Clarke & Tapia-Schythe, 2021). Since our data are clustered in 461 East German municipalities, the number of clusters is sufficiently large (more than 50) to apply the cluster-robust variance-covariance estimator (Cameron & Miller, 2015).

Using the panel event study model, we examine simultaneously the trajectories of the effects of the 2013 flood in several periods before and after the event. Specifically, we estimate the effects of the 2013 flood in one lead and three lag periods, which implies that we consider four effects simultaneously. We apply the Bonferroni method to deal with issues of multiple hypothesis testing (Shaffer, 1995). This means that we choose a significance level of 2.5% for each test so that the overall significance level is 20%. Accordingly, we present 80 % Bonferroni-corrected confidence intervals, which are equivalent to the conventional pointwise confidence intervals when the confidence level is set to 97.5%.

5 Results

We present our results in three sections. First, we present the analysis of the impact of the 2013 flood on our primary outcome, life satisfaction. Second, we delve deeper into potential underlying mechanisms by investigating the health channel and the financial channel as potential mediators through which the flood might have influenced overall life satisfaction. Finally, we extend our analysis beyond average causal effects by conducting a heterogeneity analysis, examining the flood effect for different subgroups.

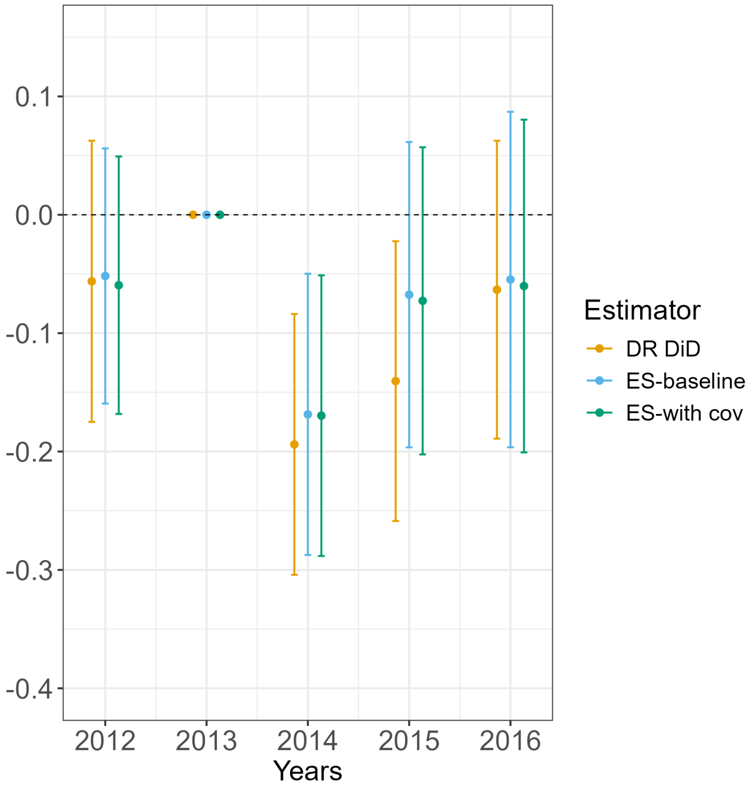
5.1 Main outcome: life satisfaction

Our results are based on two estimation strategies: a panel event study design and a doubly robust difference-in-differences estimator. Generally, both estimation strategies produce very similar results in terms of point estimates and confidence intervals. Figure 2 shows the results.[7]

We begin by assessing the plausibility of the common trend assumption, which is a crucial assumption in our panel event study design. The common trend assumption implies that the changes in life satisfaction over time among individuals who did not experience the flood can

[7]The full regression results are reported in the first column of Tables B1, B2, and B3, respectively, in the Appendix.

Figure 2: Estimated effects of experiencing the flood on life satisfaction



Note: The figure shows estimation results for one lead and three lag effects of experiencing the 2013 flood for three estimators: event study without covariates (ES baseline), event study with covariates (ES-with cov), and doubly robust difference-in-differences (DR DiD). The dependent variable is measured on an 11-point scale. Robust standard errors are clustered at the level of the municipality. The vertical lines indicate 80% Bonferroni-corrected confidence intervals.

be used as a counterfactual for those who experienced the flood. To evaluate its plausibility, we test the statistical significance of the effect of the 2013 flood on life satisfaction in the pre-treatment year 2012. If the common trend assumption holds true, we would expect a small (near zero) and statistically insignificant effect in 2012. The empirical results indeed indicate that we cannot reject the null hypothesis that the coefficient in the pre-treatment period of 2012 is zero. The coefficient is found to be statistically insignificant at all conventional levels of significance ($p = 0.35$). Moreover, the point estimate is quite small in magnitude (-0.0517), particularly when compared to the effect observed in the year after the flood.

The empirical evidence indicates that the flood has a significant impact in the first post-treatment year 2014. As a result of experiencing the flood, there is a decline in life satisfaction by 0.17 points on the 11-point scale (see Figure 2). To contextualize the magnitude of this effect, we compare it to the impact of unemployment, which is known to be a particularly detrimental life event for SWB. Research has shown that becoming unemployed is often associated with a decrease in life satisfaction of around 0.5 to 1 point on an 11-point scale (Gielen & van Ours, 2014; Kassenboehmer & Haisken-DeNew, 2009). The 0.17-point decline resulting from the flood may initially appear negligible. However, given its impact on a large population, this seemingly minor decrease implies considerable well-being loss in the community as a whole. Consequently, even a modest average reduction in SWB across a large population can result in substantial increases in healthcare needs, decreased productivity, and greater demand for social services.

Moreover, when interpreting the effect size, it is essential to consider that we estimate the effect in 2014 (i.e., the year following the flood). Therefore, we are not measuring the immediate, contemporaneous impact of the flood. We assume that the immediate effect is stronger, as a certain degree of adaptation to the event has likely already taken place one year after the flood.

We also calculate the compensating income variation (CIV) that represents the increase in household income needed to offset the negative impact of the flood on life satisfaction (for a comprehensive explanation of this concept, see Ferreira & Moro, 2010; Luechinger & Raschky, 2009).[8] For the year 2014, the CIV indicates that an increase in monthly household income of about 3,700 euros would have been required to compensate for material and psychological flood impacts on well-being.

The negative effect dissipates in the subsequent years 2015 and 2016, indicating that there is no long-term harm to life satisfaction from experiencing the flood. The flood only has a transitory effect on the life satisfaction in affected regions. This suggests that the immediate damage caused by the flood was addressed in the short term. Alternatively, the results may indicate that rapid adaptation to the flood occurred. Adaptation is a well-documented phenomenon observed

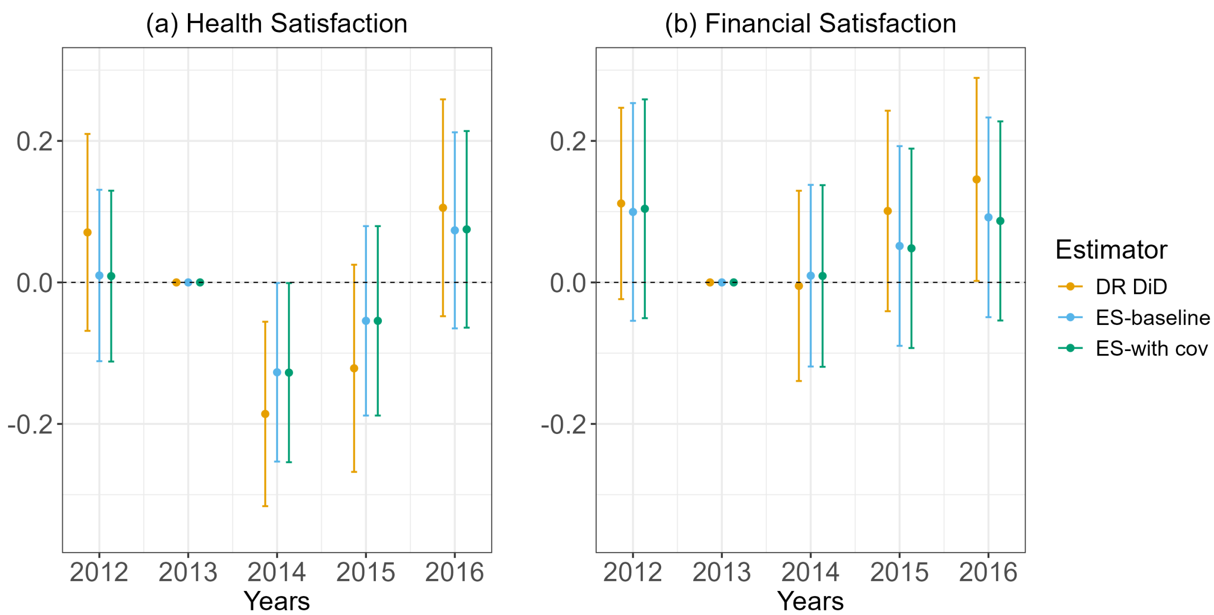
[8]The CIV is calculated as $CIV = \exp(-\delta_{2014}/\gamma)\text{income}_0 - \text{income}_0$, where γ represents the effect of the logarithm of household income on life satisfaction, δ_{2014} is the effect of the flood in 2014 (see equation 1), and income_0 denotes the income level, for which the compensation is evaluated. In a regression that incorporates both individual and year fixed effects, the point estimate for γ is 0.18. Using the average monthly household income in 2012, which is 2,350 euros, we obtain $CIV = \exp(-(-0.17)/0.18)2,350 - 2,350 = 3692.75$.

in numerous major life events (Clark et al., 2008). Additionally, the transitory decline in life satisfaction may indicate that individuals do not have lasting worries about the potential occurrence of similar disasters due to climate change. The leveling out of the flood effect might also explain why individuals affected by a flood disaster usually do not relocate (DKKV, 2013; Kox, 2016).

5.2 Mechanisms

Our study explores two distinct mechanisms by which floods may impact individuals' life satisfaction: the health channel and the financial channel. The corresponding results are displayed in Figure 3.[9]

Figure 3: Potential mechanisms



Note: The figure shows estimation results for one lead and three lag effects of experiencing the 2013 flood for three estimators: event study without covariates (ES-baseline), event study with covariates (ES-with cov), and doubly robust difference-in-differences (DR DiD). The dependent variable in both panels is measured on an 11-point scale. Robust standard errors are clustered at the level of the municipality. The vertical lines indicate 80% Bonferroni-corrected confidence intervals.

Experiencing a flood disaster can have negative consequences for the health of those affected. In addition to detrimental physical health effects, the aftermath of a natural disaster can result

[9]The full regression results for health satisfaction and financial satisfaction are reported in the second and third column of Tables B1, B2 and B3, respectively, in the Appendix.

in feelings of fear, helplessness, and grief, which can significantly affect mental health. In a comprehensive meta-analysis conducted by Keya et al. (2023), it was found that there is a clear association between disasters, including floods, and deterioration of mental health. Specifically, the occurrence of disaster events is consistently linked to an elevated prevalence of mental health disorders.

Based on our empirical findings, it appears that individuals who experience the 2013 flood exhibit a statistically significant decrease of 0.13 points in their level of health satisfaction in the first year following the flood. From 2015 onward, individuals exhibit a rapid recovery, indicating that the negative health effect in the aftermath of the 2013 flood was temporary in nature. This suggests that the initial decline in health satisfaction is not indicative of a long-lasting or chronic health impact, but rather a transitory phenomenon.

Additionally, the experience of a natural disaster can have a negative impact on individuals' life satisfaction due to the financial losses suffered, particularly the destruction of homes and possessions. To investigate this channel, we analyze the effects of the flood event on individuals' satisfaction with their financial situation. Nevertheless, in the present study, we do not observe any adverse consequences of the flood on financial satisfaction. The impact is generally considered to be statistically insignificant, and the quantitative measures of the aftermath appear to be indistinguishable from initial disparities between the treatment group and the control group before the flood event occurred.

In sum, our findings reveal a consistent pattern of the effects of the 2013 flood on both health satisfaction and life satisfaction. The effects on health satisfaction and the effects on life satisfaction are similar in magnitude and direction, suggesting that the health domain serves as an important channel through which the flood affects overall life satisfaction. In contrast, our results do not indicate a significant role of the financial domain as a transmission channel.

5.3 Heterogeneous effects

In this subsection, we examine the heterogeneity of effects across different population subgroups for life satisfaction.[10] To achieve this, we perform separate estimations for subgroups based on gender, geographical location, and income. The subgroup-specific effects are shown in Figure 4.

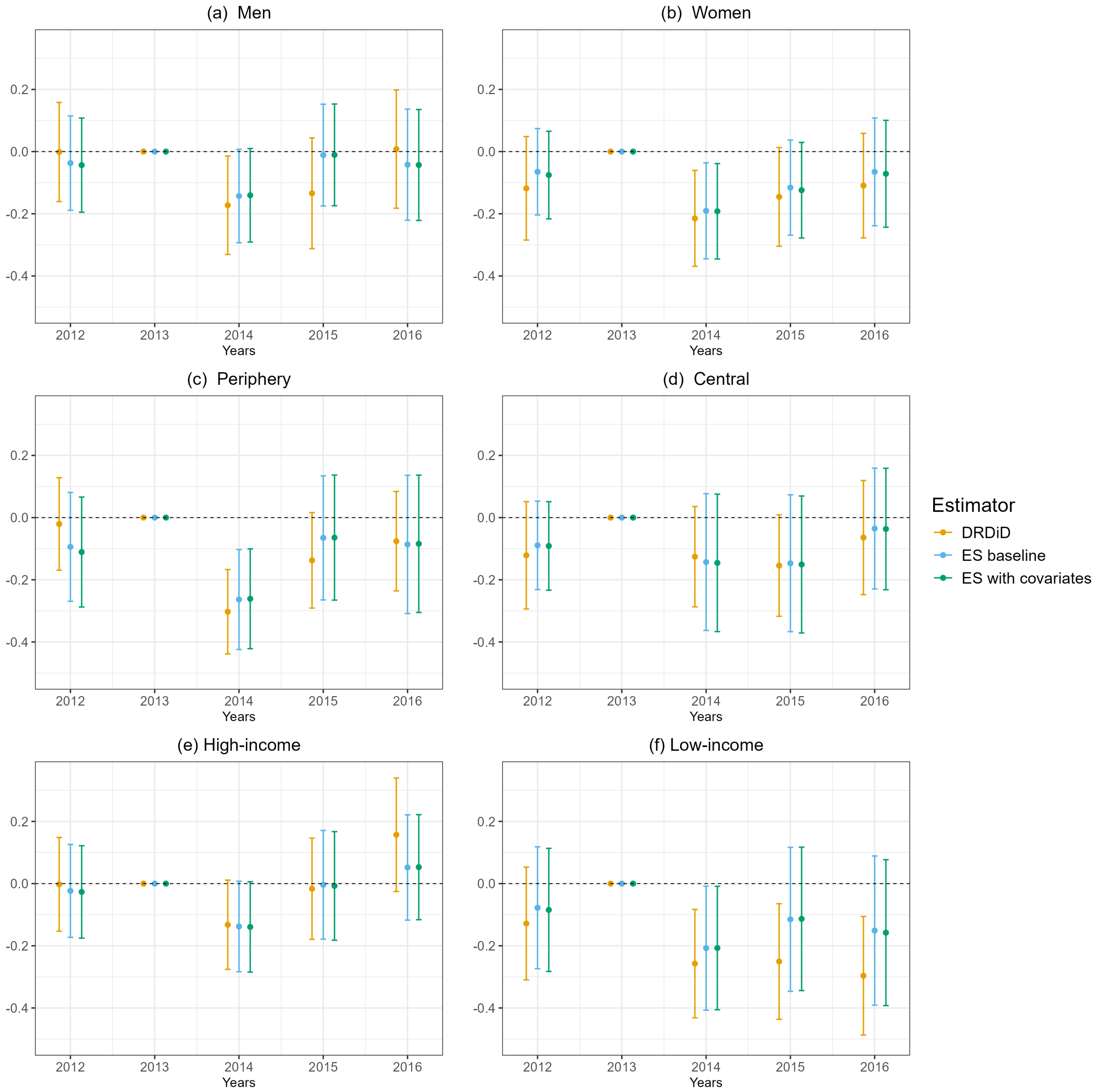
First, we investigate the gender-based heterogeneous effects of the flood on life satisfaction.[11] The findings from this analysis, as shown in Panels a and b of Figure 4, reveal that women tend to experience a slightly stronger decrease in life satisfaction compared to men. Specifically, the results obtained from the panel event study regressions indicate a decline of 0.19 points in women's life satisfaction in 2014, while men's life satisfaction decreases only by 0.14 points. Moreover, our analysis suggests that women also exhibit a slower recovery in the following years. However, it is important to note that the results should be interpreted with caution due to the wide confidence intervals and the substantial overlap between the confidence intervals of men and women. The results, therefore, do not allow us to reach a definitive conclusion regarding general gender-specific differences in the effects of experiencing a flood.

Second, we examine the heterogeneity in the flood effect on individuals' life satisfaction in peripheral and central areas. We hypothesize that the flood effects are more severe in peripheral areas than in central areas, as central areas possess more advanced infrastructure compared to peripheral areas. For instance, municipalities located in central areas often have superior flood control measures and emergency response services relative to those situated in peripheral areas (DKKV, 2013; Kuhlicke et al., 2014). Furthermore, central areas generally exhibit a more diverse economy compared to peripheral areas that often depend heavily on agriculture, livestock, and natural resources, all of which can be adversely affected by flood events.

[10] We also investigate subgroup-specific effects for health satisfaction and financial satisfaction, which are reported in Appendix A1, and A2 respectively. The regression results for the event study with covariates for health satisfaction and financial satisfaction are reported in Appendix B5, and B6, respectively.

[11] For the gender analysis, we consider the broad categories of women and men.

Figure 4: Heterogeneity analyses for life satisfaction



Note: The figure shows estimation results for one lead and three lag effects of experiencing the 2013 flood for three estimators: event study without covariates (ES baseline), event study with covariates (ES with covariates), and doubly robust difference-in-differences (DR DiD). The dependent variable is measured on an 11-point scale. Households are defined as low-income if their household equivalent income is below the median in 2012. Robust standard errors are clustered at the level of the municipality. The vertical lines indicate 80% Bonferroni-corrected confidence intervals. Sample sizes: (a) ES: 8,114; DR DiD: 7,318; (b) ES: 9,142; DR DiD: 8,335, (c) ES: 10,703; DR DiD: 9,592; (d) ES: 6,553; DR DiD: 5,981; (e) ES: 8,058; DR DiD: 7,499; (f) ES: 7,774; DR DiD: 7,174.

Another factor that may suggest differences between peripheral and central regions is the structure of home ownership. Typically, the proportion of homeowners is higher in less densely populated areas compared to more densely populated regions (Ewald et al., 2023, p. 63). As a result, residents in peripheral areas may perceive floods as a more immediate threat to their living conditions compared to those living in central regions.

The empirical findings support this hypothesis, as the analysis reveals that the flood effect is more severe in peripheral areas compared to central areas (see Panels c and d of Figure 4). The point estimates from our three models consistently demonstrate a decrease in life satisfaction of approximately 0.26 points on an 11-point scale in peripheral areas in the year following the flood. In contrast, the corresponding estimate for central areas is only about 0.15. However, by 2016, three years after the flood, we do not observe any pronounced differences in the flood effects between these areas.

Third, we split the sample by income. Respondents are categorized as high-income individuals if their equivalent household income exceeds the median in 2012, while respondents are categorized as low-income individuals if their equivalent household income is below the median.[12] The results indicate a decrease in life satisfaction in the year following the flood. This decline is more pronounced, with a decrease of 0.21 points, for individuals residing in low-income households. In contrast, individuals living in high-income households experience a smaller decline of only 0.14 points. Interestingly, the effect persists in the subsequent years of 2015 and 2016 for low-income individuals. Further analysis suggests that this may be due to heterogeneous effects on health satisfaction (see Panels e and f of Figure A1 in the Appendix). Hence, we assume that the disparity in response between low-income and high-income individuals can be attributed to lower levels of resilience among those living in low-income households.

[12] The calculation of equivalent household income is determined by dividing the total household income by the square root of the household size (OECD, 2013).

6 Sensitivity analyses

This section is dedicated to examining the sensitivity of our main results presented in section 5.1. We apply a series of sensitivity analyses with different sample restrictions: first, a sample that omits individuals who relocated between municipalities during the study period (no-movers); second, a sample that excludes neighboring municipalities of the treated (flooded) areas from the control group (no-neighbors); and third, a sample that relies solely on DLR data for identifying treated municipalities, and additionally excluding municipalities marked as flooded only in NASA data from the control group (DLR-only). Fourth, we estimate our results using an alternative treatment indicator that classifies municipalities as treated if a share of their residential area was flooded (residential). In all these sensitivity analyses, we re-estimate our results using the panel event study design, both with and without covariates, and employing the DR DiD estimator. The results of the sensitivity analyses are displayed in Figure 5.

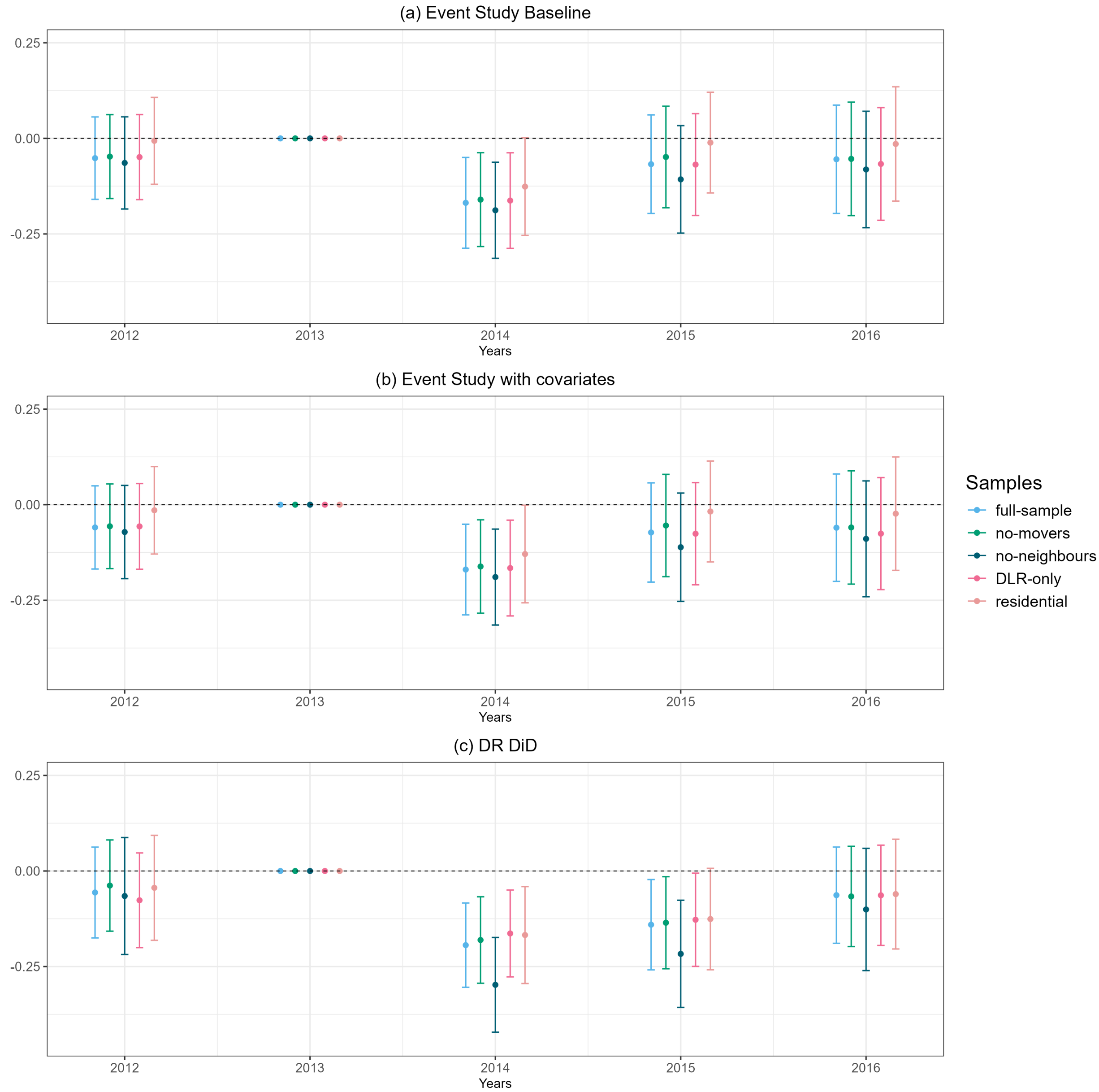
It is particularly reassuring to note that the point estimates from all these sensitivity analyses are of similar magnitude to our main results and each other. This confirms the robustness of our results with respect to different sample restrictions and definitions of the treatment indicator.

7 Conclusion

This study provides evidence on the causal effect of experiencing a natural disaster on subjective well-being. Specifically, it focuses on the 2013 flood in East Germany, a region that was severely affected. By utilizing a quasi-experimental setup and employing a panel event study design, we are able to uncover the trajectory of the flood's effect over time. To identify individuals who experienced the flood, we combine geo-spatial flood data provided by Osberghaus and Fugger (2022) with survey data obtained from the SOEP.

Our findings indicate that the 2013 flood has a significant negative effect on life satisfaction. Specifically, individuals who experienced the flood report a decline in life satisfaction by 0.17

Figure 5: Sensitivity analyses



Note: The figure shows estimation results for the sensitivity analyses. The dependent variable is measured on an 11-point scale. Robust standard errors are clustered at the level of the municipality. The vertical lines indicate 80% Bonferroni-corrected confidence intervals. Sample sizes in parentheses: no-movers (ES: 16,473; DR DiD: 14,981), no-neighbours (ES: 14,568; DR DiD: 13,220), DLR-only (ES: 16,383; DR DiD: 14,821), residential (ES: 15,490; DR DiD: 13,983).

points on an 11-point scale in the year following the flood, on average. This corresponds to a 2.5% decrease compared to the average life satisfaction before the flood occurred. However, the negative effect dissipates in the subsequent years 2015 and 2016. Our findings suggest that a primary mechanism through which the flood influenced life satisfaction was the decline in health satisfaction. In the first year after the flood, individuals reported a decrease in health satisfaction by 0.13 points on an 11-point scale, for which we also observe a swift recovery starting from 2015 onwards. Our results did not indicate a decline in financial satisfaction as a result of experiencing the flood.

We conduct three heterogeneity analyses to explore variations in the effect of the 2013 flood in different subgroups of the population. First, we do not find significant evidence of gender-specific differences. Second, we examine the geographical location aspect by distinguishing between peripheral and central areas. In this analysis, we observe that the immediate impact of the flood was more severe in peripheral areas. We posit that central areas are better equipped to deal with the adverse effects of the disaster due to their superior flood control measures and emergency response services. Moreover, central areas may have a more diverse economy compared to peripheral areas, which often heavily rely on agriculture, livestock, and natural resources—all of which can be significantly impacted by a flood. Third, when we split the sample by income, we find that individuals with low incomes experienced a more pronounced decrease in life satisfaction than individuals with high incomes. This disparity is likely due to lower levels of resilience among those with lower incomes.[13]

Our findings remain robust when different estimation methods and sample restrictions are employed. Specifically, we utilized various estimation frameworks, such as the DiD event study design and the doubly robust estimator. Additionally, we imposed different sample restrictions, including the DLR-only subsample, exclusion of movers and neighboring municipalities. Also, we used an alternative definition of the treatment indicator that is based on whether any part of the municipality's residential area was affected by flooding. Overall, the results obtained from different estimators and sample restrictions exhibit a high degree of similarity.

[13]The decline among low-income individuals does not seem to be directly attributed to financial resources, as the flood did not result in a differing response in financial satisfaction between the two groups.

This research is important for informing policy decisions in natural disaster management, specifically for floods. One conclusion from our research is to increase public awareness about the short-term impact of floods on subjective well-being in general, and the health channel in particular. By informing communities about the resilience of specific groups, policymakers can develop initiatives to provide support and assistance particularly targeted at low-income households. This can include implementing counseling services and (mental) health support to promote psychological well-being in the direct aftermath of floods. The short-term nature of the effect may also be informative for understanding reconstruction decisions and the implementation of precautionary measures. The swift dissipation of the negative effects of the floods may indicate a certain degree of repression, which in turn could close the window of opportunity for the implementation of long-term measures in the political arena quite soon. In this instance, adaptation may even prove to be an obstacle to adjustment.

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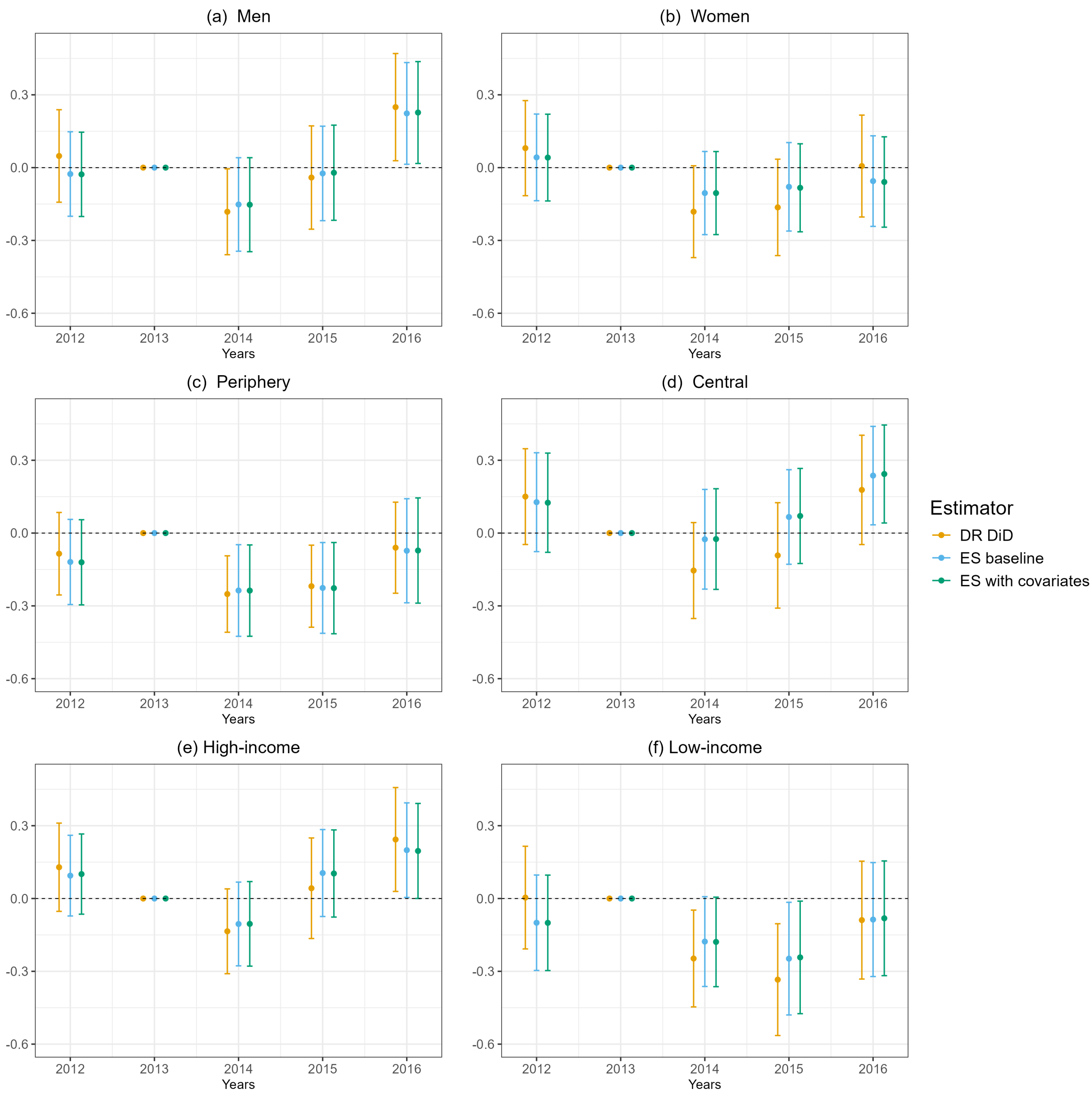
Appendix for

Rising waters, falling well-being: The effects of the 2013 East German flood on subjective well-being

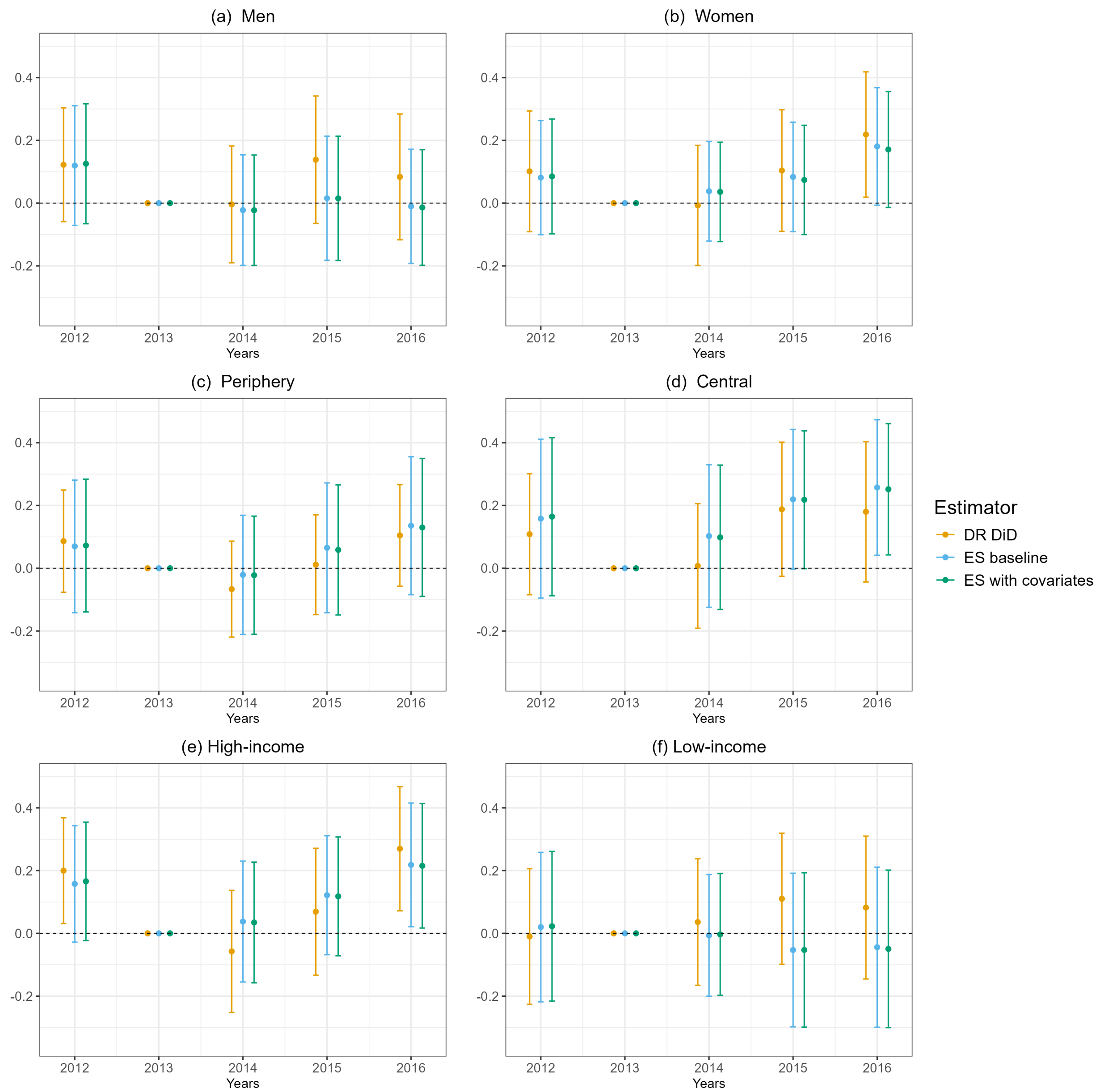
Contents

Figure A1: Heterogeneity analyses for health satisfaction



Note: The figure shows estimation results for one lead and three lag effects of experiencing the 2013 flood for three estimators: event study without covariates (ES baseline), event study with covariates (ES with covariates), and doubly robust difference-in-differences (DR DiD). The dependent variable is measured on an 11-point scale. Households are defined as low-income if their household equivalent income is below the median in 2012. Robust standard errors are clustered at the level of the municipality. The vertical lines indicate 80% Bonferroni-corrected confidence intervals. Sample sizes: (a) ES: 8,114; DR DiD: 7,318; (b) ES: 9,142; DR DiD: 8,335, (c) ES: 10,703; DR DiD: 9,592; (d) ES: 6,553; DR DiD: 5,981; (e) ES: 8,058; DR DiD: 7,499; (f) ES: 7,774; DR DiD: 7,174.

Figure A2: Heterogeneity analyses for financial satisfaction



Note: The figure shows estimation results for one lead and three lag effects of experiencing the 2013 flood for three estimators: event study without covariates (ES baseline), event study with covariates (ES with covariates), and doubly robust difference-in-differences (DR DiD). The dependent variable is measured on an 11-point scale. Households are defined as low-income if their household equivalent income is below the median in 2012. Robust standard errors are clustered at the level of the municipality. The vertical lines indicate 80% Bonferroni-corrected confidence intervals. Sample sizes: (a) ES: 8,114; DR DiD: 7,318; (b) ES: 9,142; DR DiD: 8,335, (c) ES: 10,703; DR DiD: 9,592; (d) ES: 6,553; DR DiD: 5,981; (e) ES: 8,058; DR DiD: 7,499; (f) ES: 7,774; DR DiD: 7,174.

Table B1: Estimation results event study without covariates

	Life satisfaction	Health satisfaction	Financial satisfaction
treated×2012	-0.0517	0.0098	0.0996
	(0.0550)	(0.0618)	(0.0785)
treated×2014	-0.1686***	-0.1270**	0.0095
	(0.0606)	(0.0647)	(0.0655)
treated×2015	-0.0675	-0.0543	0.0515
	(0.0658)	(0.0683)	(0.0720)
treated×2016	-0.0547	0.0736	0.0920
	(0.0723)	(0.0707)	(0.0720)
2012	-0.0650	0.0442	-0.1632***
	(0.0401)	(0.0439)	(0.0524)
2014	0.0844**	0.0442	0.1452***
	(0.0399)	(0.0405)	(0.0411)
2015	0.1456***	-0.0036	0.3054***
	(0.0494)	(0.0407)	(0.0496)
2016	0.1317***	-0.1062**	0.3688***
	(0.0448)	(0.0457)	(0.0522)
Compensating income variation in 2014:			
	3,646 €		
Observations	17,256	17,256	17,256

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses, clustered at the municipality level. The analysis encompasses the time period from 2012 to 2016. 2013 is the baseline year. All regressions include individual fixed effects.

Table B2: Estimation results event study with covariates

	Life satisfaction	Health satisfaction	Financial satisfaction
treated×2012	-0.0595	0.0089	0.1041
	(0.0555)	(0.0616)	(0.0789)
treated×2014	-0.1697***	-0.1275**	0.0091
	(0.0605)	(0.0646)	(0.0655)
treated×2015	-0.0727	-0.0543	0.0482
	(0.0662)	(0.0683)	(0.0719)
treated×2016	-0.0602	0.0750	0.0869
	(0.0717)	(0.0709)	(0.0718)
2012	-0.0664*	0.0468	-0.1657***
	(0.0401)	(0.0438)	(0.0523)
2014	0.0874**	0.0428	0.1466***
	(0.0400)	(0.0405)	(0.0415)
2015	0.1540***	-0.0073	0.3086***
	(0.0498)	(0.0407)	(0.0495)
2016	0.1460***	-0.1115**	0.3733***
	(0.0459)	(0.0455)	(0.0526)
education	0.0565	0.1151*	0.0647
	(0.0541)	(0.0642)	(0.1252)
single	-0.0718	-0.0379	0.0255
	(0.1290)	(0.1471)	(0.1612)
divorced	0.1936	0.0830	0.2150
	(0.1437)	(0.2034)	(0.1719)
widowed	-0.9508***	-0.1203	0.3519
	(0.1787)	(0.1571)	(0.2218)
household size	0.0145	-0.0089	0.1168***
	(0.0420)	(0.0351)	(0.0419)
rural	0.1345	0.2034	0.2557
	(0.3098)	(0.3289)	(0.3047)
periphery	-0.0477	-0.2413	-0.0933
	(0.1589)	(0.1644)	(0.2793)
rural×periphery	-0.1608	0.0596	0.1019
	(0.3194)	(0.3734)	(0.3918)
Compensating income variation in 2014:			
	3,683 €		
Observations	17,256	17,256	17,256

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses, clustered at the municipality level. The analysis encompasses the time period from 2012 to 2016. 2013 is the baseline year. All regressions include individual fixed effects.

Table B3: Estimation results DR DiD

	Life satisfaction	Health satisfaction	Financial satisfaction
2013	0.0562	-0.0707	-0.1116
	(0.0606)	(0.0710)	(0.0690)
2014	-0.1940***	-0.1859***	-0.0049
	(0.0562)	(0.0665)	(0.0686)
2015	-0.1405**	-0.1214	0.1010
	(0.0603)	(0.0747)	(0.0723)
2016	-0.0633	0.1055	0.1456**
	(0.0642)	(0.0782)	(0.0732)
Compensating income variation in 2014:			
	4,555 €		
Observations	15,653	15,653	15,653

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses. The analysis encompasses the time period from 2012 to 2016.

Table B4: Heterogeneity analyses of life satisfaction event study with covariates

	Gender		Geographical Location		Income	
	Female	Male	Central	Periphery	Low-income	High-income
treated×2012	-0.0755	-0.0436	-0.0912	-0.1108	-0.0846	-0.0267
	(0.0719)	(0.0773)	(0.0726)	(0.0902)	(0.1010)	(0.0758)
treated×2014	-0.1920**	-0.1405*	-0.1456	-0.2611***	-0.2072**	-0.1393*
	(0.0783)	(0.0767)	(0.1128)	(0.0819)	(0.1013)	(0.0742)
treated×2015	-0.1242	-0.0106	-0.1508	-0.0644	-0.1134	-0.0074
	(0.0784)	(0.0835)	(0.1124)	(0.1026)	(0.1177)	(0.0891)
treated×2016	-0.0714	-0.0431	-0.0367	-0.0843	-0.1577	0.0529
	(0.0877)	(0.0910)	(0.0997)	(0.1127)	(0.1197)	(0.0862)
2012	-0.0694	-0.0641	0.0039	-0.0823*	-0.0658	-0.0958*
	(0.0503)	(0.0519)	(0.0620)	(0.0488)	(0.0554)	(0.0496)
2014	0.1316***	0.0342	0.1233	0.0775*	0.1035*	0.0501
	(0.0464)	(0.0548)	(0.1025)	(0.0429)	(0.0575)	(0.0475)
2015	0.2157***	0.0802	0.2364**	0.1326**	0.1846**	0.0734
	(0.0529)	(0.0648)	(0.1037)	(0.0579)	(0.0720)	(0.0538)
2016	0.1765***	0.1088*	0.1142	0.1560***	0.2492***	0.0054
	(0.0543)	(0.0620)	(0.0730)	(0.0546)	(0.0735)	(0.0553)
education	0.0534	0.0590	0.0453	0.0684	0.0307	0.0797
	(0.0687)	(0.0720)	(0.0796)	(0.0815)	(0.0940)	(0.0685)
single	-0.0392	-0.1105	-0.1958	0.0396	-0.3178	0.1516
	(0.1927)	(0.1379)	(0.1694)	(0.1961)	(0.2350)	(0.1425)
divorced	0.3246	0.0476	-0.0714	0.3786**	0.1784	0.2814
	(0.2289)	(0.1978)	(0.2374)	(0.1775)	(0.1967)	(0.2572)
widowed	-0.8055***	-1.6577***	-0.5391*	-1.1397***	-1.2466***	-0.6663***
	(0.1888)	(0.4179)	(0.3099)	(0.2129)	(0.2698)	(0.2581)
household size	0.0123	0.0157	-0.0206	0.0419	-0.0603	0.0632
	(0.0521)	(0.0487)	(0.0930)	(0.0436)	(0.0616)	(0.0453)
rural	-0.2609	0.7996	-0.2374	-0.0159	-0.7997	0.6992*
	(0.3359)	(0.5333)	(0.3752)	(0.1667)	(0.5928)	(0.3736)
periphery	-0.1751	0.1157			-0.5343*	0.1221
	(0.2250)	(0.1829)			(0.2938)	(0.2749)
rural×periphery	0.3153	-0.9786*			0.8919	-0.8733**
	(0.3620)	(0.5596)			(0.6132)	(0.4205)
Observations	9,142	8,114	6,553	10,703	7,774	8,058

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses, clustered at the municipality level. The analysis encompasses the time period from 2012 to 2016. 2013 is the baseline year. The dependent variable is measured on an 11-point scale. Households are defined as low-income if their household equivalent income is below the median in 2012. All regressions include individual fixed effects.

Table B5: Heterogeneity analyses of health satisfaction event study with covariates

	Gender		Geographical Location		Income	
	Female	Male	Central	Periphery	Low-income	High-income
treated×2012	0.0414	-0.0277	0.1251	-0.1204	-0.1002	0.1007
	(0.0912)	(0.0886)	(0.1043)	(0.0895)	(0.1003)	(0.0843)
treated×2014	-0.1048	-0.1527	-0.0247	-0.2370**	-0.1788*	-0.1044
	(0.0873)	(0.0988)	(0.1058)	(0.0960)	(0.0941)	(0.0889)
treated×2015	-0.0831	-0.0210	0.0705	-0.2269**	-0.2426**	0.1031
	(0.0925)	(0.1000)	(0.0999)	(0.0959)	(0.1183)	(0.0916)
treated×2016	-0.0592	0.2270**	0.2434**	-0.0719	-0.0815	0.1960**
	(0.0950)	(0.1071)	(0.1030)	(0.1106)	(0.1206)	(0.0999)
2012	0.0396	0.0558	0.0010	0.0646	0.0731	0.0063
	(0.0591)	(0.0554)	(0.0907)	(0.0497)	(0.0711)	(0.0532)
2014	0.0297	0.0574	0.0087	0.0546	0.0726	-0.0032
	(0.0548)	(0.0541)	(0.0885)	(0.0452)	(0.0594)	(0.0593)
2015	0.0440	-0.0654	-0.0177	-0.0048	0.0335	-0.0509
	(0.0573)	(0.0562)	(0.0848)	(0.0461)	(0.0669)	(0.0587)
2016	-0.0296	-0.2051***	-0.2080**	-0.0871*	-0.0424	-0.2002***
	(0.0587)	(0.0626)	(0.0877)	(0.0524)	(0.0669)	(0.0652)
education	0.2076**	0.0331	0.1046	0.1417	0.1169	0.0816
	(0.0861)	(0.0901)	(0.0658)	(0.1302)	(0.0931)	(0.0996)
single	0.0606	-0.1361	0.0064	-0.0593	-0.1078	0.0557
	(0.2307)	(0.1640)	(0.1804)	(0.2301)	(0.2513)	(0.1966)
divorced	0.1619	-0.0060	-0.3701	0.4193	0.1418	0.1676
	(0.2422)	(0.3302)	(0.2668)	(0.2748)	(0.2777)	(0.3433)
widowed	-0.1895	0.1847	-0.1423	-0.0727	-0.3069	0.1377
	(0.1738)	(0.4255)	(0.2762)	(0.1941)	(0.2156)	(0.2416)
household size	0.0193	-0.0395	-0.0227	0.0061	-0.1072**	0.0598
	(0.0513)	(0.0464)	(0.0488)	(0.0524)	(0.0509)	(0.0557)
rural	0.1784	0.2421	0.1462	0.1628	0.1211	0.6521*
	(0.4949)	(0.4481)	(0.4322)	(0.2159)	(0.6052)	(0.3795)
periphery	-0.1457	-0.3201**			-0.6968***	0.4510
	(0.2736)	(0.1616)			(0.2618)	(0.3120)
rural×periphery	-0.0069	0.1169			0.5549	-1.1299**
	(0.5512)	(0.4902)			(0.6182)	(0.5244)
Observations	9,142	8,114	6,553	10,703	7,774	8,058

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses, clustered at the municipality level. The analysis encompasses the time period from 2012 to 2016. 2013 is the baseline year. All regressions include individual fixed effects. The dependent variable is measured on an 11-point scale. Households are defined as low-income if their household equivalent income is below the median in 2012.

Table B6: Heterogeneity analyses of financial satisfaction event study with covariates

	Gender		Geographical Location		Income	
	Female	Male	Central	Periphery	Low-income	High-income
treated×2012	0.0852	0.1256	0.1643	0.0724	0.0227	0.1658*
	(0.0933)	(0.0975)	(0.1285)	(0.1079)	(0.1217)	(0.0962)
treated×2014	0.0359	-0.0226	0.0985	-0.0222	-0.0033	0.0347
	(0.0808)	(0.0898)	(0.1174)	(0.0960)	(0.0990)	(0.0981)
treated×2015	0.0740	0.0152	0.2183*	0.0585	-0.0529	0.1180
	(0.0888)	(0.1010)	(0.1121)	(0.1057)	(0.1255)	(0.0966)
treated×2016	0.1710*	-0.0138	0.2518**	0.1299	-0.0494	0.2153**
	(0.0943)	(0.0941)	(0.1068)	(0.1121)	(0.1280)	(0.1012)
2012	-0.1265*	-0.2090***	-0.2451**	-0.1349**	-0.1995**	-0.1424**
	(0.0652)	(0.0614)	(0.1053)	(0.0607)	(0.0852)	(0.0596)
2014	0.1768***	0.1146**	0.0680	0.1609***	0.2046***	0.0495
	(0.0592)	(0.0499)	(0.0993)	(0.0460)	(0.0665)	(0.0642)
2015	0.3513***	0.2648***	0.1030	0.3566***	0.5089***	0.1111**
	(0.0667)	(0.0659)	(0.0922)	(0.0569)	(0.0882)	(0.0567)
2016	0.3814***	0.3658***	0.1545	0.4145***	0.6044***	0.1498**
	(0.0686)	(0.0663)	(0.0946)	(0.0615)	(0.0883)	(0.0700)
education	0.1062	0.0175	-0.0675	0.1503	0.0538	-0.0150
	(0.1433)	(0.1721)	(0.1841)	(0.1386)	(0.2065)	(0.1556)
single	-0.0291	0.0948	0.3194***	-0.0802	0.2038	0.3064
	(0.2314)	(0.1898)	(0.1174)	(0.2734)	(0.2784)	(0.1887)
divorced	0.2575	0.1924	-0.0264	0.4315**	0.3798	-0.1935
	(0.2804)	(0.2217)	(0.2904)	(0.1938)	(0.2806)	(0.2040)
widowed	0.1482	1.3332	0.3562	0.3370	0.4053	0.3145
	(0.2481)	(0.4025)	(0.5114)	(0.2483)	(0.2938)	(0.3552)
household size	0.1622***	0.0731	0.1970***	0.0857	0.1544**	0.1032
	(0.0551)	(0.0566)	(0.0711)	(0.0532)	(0.0634)	(0.0642)
rural	0.3268	0.0072	0.2847	0.4731*	0.2137	0.3585
	(0.4248)	(0.3144)	(0.4310)	(0.2728)	(0.5559)	(0.3249)
periphery	-0.0551	-0.1564			-0.0294	-0.4835
	(0.4259)	(0.3262)			(0.4378)	(0.4770)
rural×periphery	-0.2792	0.7531*			0.5604	-0.2237
	(0.5384)	(0.4415)			(0.5689)	(0.5769)
Observations	9,142	8,114	6,553	10,703	7,774	8,058

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses, clustered at the municipality level. The analysis encompasses the time period from 2012 to 2016. 2013 is the baseline year. All regressions include individual fixed effects. The dependent variable is measured on an 11-point scale. Households are defined as low-income if their household equivalent income is below the median in 2012.