Weather-Related House Damage and Subjective Wellbeing

by

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Abstract

Climate change is causing weather-related natural disasters to become both more frequent and more severe. We contribute to the literature that estimates the economic impact of these disasters by using Australian data for the period 2009 to 2018 to estimate the impact of experiencing weather-related house damage on three measures of subjective wellbeing. While there is some evidence that poor people experience a sizeable and statistically significant decrease in subjective wellbeing following weather-related house damage, we find little evidence of a significant or sizable effect on average. In contrast, we find that, on average, both separation and job loss have a large and statistically significant impact on subjective wellbeing.

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I.   Introduction

Climate change is causing an increase in both the frequency and severity of weather related natural disasters (World Meteorological Organization, 2014). In fact, the number of weather related natural disasters per decade rose by over 370% between 1971 and 2010 (World Meteorological Organization, 2014).

The traditional approach to estimate the economic impact of such disasters focuses on the flow of GDP, primarily because it is widely available and consistently measured across countries. Unfortunately, it has well known weaknesses in the context of disaster impact measurement. Firstly, GDP itself may increase after a disaster due to the rebuild effort which would be captured by this measurement approach, however the associated opportunity costs associated would be ignored. Secondly, it ignores many of the impacts from natural disasters, such as asset loss, psychological costs, environmental harm, and loss of life.

Due to these factors, it is commonly agreed that most estimates substantially underestimate the true impact of natural disasters (Deloitte, 2016; Hallegatte, 2015; Hallegatte & Przyluski, 2010; Hochrainer, 2009; Kousky, 2014; Sheng & Xu, 2019). It is thus natural to look for alternative techniques which can address some of these issues and complement the more traditional income-based approach.

A relatively new strand of economic literature focuses on measuring the impact of disasters by analysing the change in subjective wellbeing (Carroll et al., 2009; Luechinger & Raschky 2009,; Calvo et al., 2015; Sekulova & van den Bergh, 2016; Lohmann et al., 2019). In this paper, we contribute to this literature by using 10 years' worth of individual level panel data to estimate the impact of experiencing weather-related house damage on subjective wellbeing in Australia. In addition to using a better dataset, we make two key contributions to the existing literature. Firstly, following the method suggested by Bloem (2018), we perform a series of data transformations to empirically examine whether our results are robust to changes in the assumed underlying cardinal scale. This approach helps moderate concerns raised by Bond & Lang (2019) about the appropriateness of using aggregated subjective wellbeing data and also helps provide extra confidence in our results. Secondly, we also examine the wellbeing effect of two additional life events: relationship breakup and

involuntary loss of job. We compare the size of the wellbeing effect of experiencing these events against the wellbeing effect of experiencing weather-related house damage. This helps provide some additional perspective about how small or large the estimated wellbeing effect from weather-related house damage is.

We find that experiencing weather-related house damage has a wellbeing effect which is small in magnitude for all those except the poor and is frequently statistically insignificant. In contrast, we find that experiencing either job loss or a relationship breakup is associated with a significant and large decrease in wellbeing. More specifically, our main analysis shows that that experiencing weather-related house damage explains at most 12% of a within-person standard deviation of subjective wellbeing. Experiencing a relationship breakup can explain over 48% of a within-person standard deviation of wellbeing, while involuntary loss of job can explain as much as 28% of a within-person standard deviation. Our conclusions are generally robust to three different measures of wellbeing and a variety of assumed underlying cardinalizations.

The rest of the paper is structured as follows. Section 2 discusses the literature on wellbeing and the wellbeing effect of weather-related disasters. Section 3 presents the data used in the analysis, section 4 the methodology, and section 5 the results. Section 6 provides a broader discussion of these results, while section 7 concludes.

II.   Wellbeing and weather-related disasters

Economic theory often assumes that people are rational expected utility maximisers. Utility itself is unable to be directly measured but it is often assumed that income can be used as a proxy. The classical view among most economists is that not only does an increase in income increase utility, but absolute income alone can be used to measure utility (Stutzer, 2004). This view of absolute income being the sole proxy measure of utility has been criticized for being too narrow and for ignoring the importance of other factors in affecting wellbeing.

A relatively new but rapidly increasing strand of literature has focused on using self-reported subjective wellbeing as a direct measure of utility (Clark et al., 2008). A variable has to meet two requirements for it to be used as a proxy measure of utility: a strong theoretical basis for why it should be related to utility, and a reliable way to measure it. While there is widespread consensus that people treat wellbeing, rather than income, as their life objective (Frey &

Stutzer, 2002; Rehdanz & Maddison, 2005), whether subjective wellbeing can actually be accurately and reliably measured is, perhaps not surprisingly, a more controversial issue. Many have argued, however, that most individuals can accurately evaluate their own subjective wellbeing, and that self-reported subjective wellbeing is a reliable measure of true subjective wellbeing (Di Tella & MacCulloch, 2006; Ferrer-i-Carbonell, 2013; Hayo, 2007).[1]

While an enormous wealth of factors which have the potential to influence happiness have been identified in academic literature (see Dolan et al. (2008) for a comprehensive review of what influences subjective wellbeing), there is only a limited literature which focuses on the effect of weather related events on subjective wellbeing. Moreover, no strong consensus view has so far emerged, with some studies finding large negative effects while others have found no significant impact.

Sekulova & van den Bergh (2016) analysed flood data from Bulgaria and found a significant and persistent drop in subjective wellbeing, a drop which is further relatively homogenous across different groups. Similarly, Lohmann et al. (2019) used cross-sectional data from Papua New Guinea and found that experiencing disaster related damage caused a significant drop in subjective wellbeing, but also that those who experienced the disaster but suffered no damage experienced no loss in wellbeing.

Other studies have found experiencing a weather-related natural disaster has no significant lasting impact on wellbeing. For example, Calvo et al. (2015) used panel data to examine the impact of Hurricane Katrina on the happiness of women. While they found a significant short-term drop in wellbeing, they also found the effect was short-lived, social support playing an important role in long-term wellbeing recovery.[2] Luechinger & Raschky (2009) analysed 16 European countries over a 25 year period and found floods caused a large drop in subjective wellbeing, although by 18 months after the disaster the estimated effect was small and less than 20% of the estimated 6 month effect. Importantly, they also found the availability of risk-

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[1] These are not identical concepts. It is possible for an individual to be able to accurately assess his own wellbeing but to consistently report it incorrectly.

[2] They noted that about 8% of their sample did not recover from the immediate drop in happiness, which was correlated with living alone and a lack of community support both before and after Hurricane Katrina occurred (Calvo et al., 2015).

transfer schemes[3] had large mitigating effects which almost offset the negative wellbeing effects of any disasters.[4]

Two papers focus on the impact of weather-related natural disasters in Australia. Carroll et al. (2009) used quarterly rainfall measures to estimate the impact of drought in Australia between 2001 and 2004. They find that spring drought causes a large loss of wellbeing for rural communities but has no effect on urban communities, while drought in other seasons has no significant effect at all. The authors note that this relatively short time period included an especially severe drought which occurred in 2002 (Carroll et al., 2009). It is at least possible that their estimate is thus more an estimate of that particular event than general drought. Baryshnikova & Pham (2018) used HILDA data[5] and a quantile approach to estimate the mental health effects (measured using the Mental Health Component Summary Score) of a weather-related natural disaster and found negative effects for homeowners and those with poor pre-existing mental health.

Our research differs from these the existing literature in several ways. First, our study uses a large scale, nationally representative, individual level panel dataset which allows us to control for individual level fixed effects. Calvo et al. (2015) is the only other study that focuses on SWB and uses 3 waves of individual level panel survey data for about 1000 low-income parents who were full-time students at two New Orleans community colleges. This paper uses 10 waves of an individual level panel survey of about 24000 individuals, a sample representative of the Australian population. Other studies that focus on SWB either use cross-sectional data at a single point in time, or repeated cross-sectional data.[6] They thus can control for fixed effects only at the regional level. Second, we compare the impact on wellbeing from experiencing weather-related house damage to the impact from either

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[3] They note the imperfections of private insurance in the case of a natural disaster, and instead refer to mandatory disaster insurance and emergency post disaster relief as risk transfer schemes (Luechinger & Raschky, 2009).

[4] In fact, the effect of a disaster on wellbeing was not significantly different from zero given the presence of risk transfer schemes (Luechinger & Raschky, 2009).

[5] We also use HILDA data in this thesis. For more details on HILDA see section 3.

[6] Compared to the other studies that focus on Australia, we use a much longer period of data which contains a much wider set of severe weather events than Carroll et al., (2009). While we use the same explanatory variable and dataset as Baryshnikova & Pham (2018), we focus on subjective wellbeing as opposed to mental health. Note that (Johar & al., 2020) use the HILDA dataset to estimate the impact of WRHD on income and find no average impact.

separation or involuntary job loss. Finally, we perform the robustness check data transformations as suggested by Bloem (2018).

III.   Data and Data Transformations

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) survey to estimate the impact of weather-related house damage on people's happiness in Australia. HILDA is a yearly household-based longitudinal survey which was first collected in 2001 and currently consists of 18 years of data from 2001 to 2018. HILDA contains a wide variety of information and is designed to facilitate research into three primary areas: income, labour market and family dynamics (Department of Social Services; Melbourne Instituse of Applies Economic and Social Research, 2019). According to two of the lead survey designers,

> "The Household, Income and Labour Dynamics in Australia (HILDA) Survey is one of only a small number of well-established, large, nationally-representative household panel studies conducted in the world" (Watson & Wooden, 2012, pp. 369).

HILDA contains two variables of particular relevance to this research. Since 2001, HILDA has asked respondents to evaluate their overall life satisfaction, with responses given on a 0-10 scale. Since 2009, HILDA has asked each respondent whether their house has been damaged or destroyed by a weather-related disaster within the last 12 months. We use these responses as our primary dependent variable and independent variable, respectively. The dataset contains 144,784 observations of 23,740 people, implying each person is interviewed approximately six times on average.

There is some debate within the literature surrounding the distinction between happiness and life satisfaction, with the resulting possibility that superficially similar questions may lead to differing results. Because of this, we also include two alternative dependent variables collected by the HILDA survey which we use to check the robustness of our findings. These alternative variables are happiness, as measured by how much time in the last four weeks the respondent has been happy (with 1 meaning none of the time and 6 meaning all the time), and satisfaction with the home the respondent lives in (a score between 0 and 10). We also

include variables from the HILDA survey which record whether the respondent has had a relationship end within the last 12 months or has lost their job within the last 12 months. We use these as alternative independent variables to provide a measure of comparison as to how large the wellbeing impact of a disaster is relative to other major life events.[7] In addition, we include age and the square of age as control variables.

It is possible that different groups of people are affected differently by a weather-related disaster. Due to this possibility, we create and include four binary variables to subset the data on.[8] These binary variables are gender, homeownership status, family prosperity, and treatment status. Gender is 1 if the person is a male, and 0 if the person is a female. Homeownership status is 1 if the person is a homeowner, and 0 otherwise. Family prosperity is 1 if the person self-reported as being either "prosperous", "very comfortable", or "reasonably comfortable", and is 0 if the person self-reported as being either "just getting along", "poor", or "very poor". Finally, treatment status is 1 if the person ever experienced weather-related house damage and is 0 otherwise.[9] Descriptive statistics for all variables are presented in Table .

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[7] Within-year correlations between these 3 variables are relatively modest and range from 0.23 to 0.5. Within-person correlations over time are even lower, with average correlations ranging from 0.08 to 0.25. Perhaps not surprisingly, the distribution of within-person correlation is very dispersed, while the distribution of within-year correlation is very tight.

[8] We choose to subset the data on these variables due to the strong possibility of interaction effects. It is very plausible that experiencing weather-related house damage affects different groups of people differently. For this reason, it is preferable to subset rather than include these variables as control variables.

[9] Throughout this paper, the "ever treated" sample refers to all those who ever experienced weather-related house damage.

Table 1: Descriptive Statistics

	Full Sample		Ever Treated Subsample	
	Mean	Standard Deviation	Mean	Standard Deviation
Weather Damage	0.015	0.121	0.156	0.363
Life Satisfaction	7.937	1.423	7.840	1.506
Happiness	4.385	1.090	4.301	1.111
House Satisfaction	8.008	1.740	7.901	1.807
Job Loss	0.033	0.178	0.039	0.195
Separation	0.035	0.183	0.038	0.191
Homeowner	0.691	0.462	0.701	0.456
Wealth Status	0.700	0.458	0.645	0.478
Male	0.468	0.499	0.478	0.500
Age	45.11	18.72	46.42	17.31
Ever Treated	0.095	0.294	1	0

It's worth noting that one average respondents have high levels of wellbeing and that substantially more respondents experienced job loss and separation than experienced weather-related house damage.

In the past, the reliability and validity of self-reported subjective wellbeing among individuals was assumed[10] to validate the use of this measure in groups, with the underlying assumption being that validity at the individual level ensured validity at the aggregate level. Effectively, it was believed that the aggregated wellbeing score of Group 1 could be compared to the aggregated utility score of Group 2. However, more recently, this has become a point of contention, with the discussion centring around the legitimacy of ranking aggregated ordinal data.

It is widely accepted that subjective wellbeing data is ordinal, rather than cardinal, in nature. Despite this, a significant proportion of happiness researchers treat subjective wellbeing data as cardinal and thus use ordinary least squares to perform their analysis (Schröder & Yitzhaki, 2017). Researchers who are unwilling to assume cardinality instead usually use ordered probit or logit models in their research. Typically though, ordinal models have returned similar estimates to cardinal methods (Ferrer-i-Carbonell & Frijters, 2004). Overall, the similarity of

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[10] This assumption was often implicit rather than explicit.

empirical results between cardinal and ordinal models has led many to conclude that, for subjective wellbeing data, the distinction between cardinality and ordinality is unimportant (Schröder & Yitzhaki, 2017).

Recent literature has challenged this assumption, showing that common models may produce unreliable results when applied to ordinal data. Bond & Lang (2019) show that it is effectively impossible to rank two groups in order of happiness. A monotonic transformation which is rank preserving at the individual level can almost always be found which will change the rank at a group level[11]. This also means that two monotonic transformations which are individually rank preserving can be found which provide coefficient estimates of the opposite sign. We provide a simple two-person example of this in Table 2. At the original scale, the group means of Group 1 and Group 2 are identical. However, this is fragile to a change in the underling scale. Applying a monotonically increasing convex transformation results in Group 1 having a higher mean than Group 2, while a monotonically increasing concave transformation has the opposite effect.

Table 2: Data Transformation Example

| | Group 1 | | | Group 2 | | |
	Original	Convex Transform	Concave Transform	Original	Convex Transform	Concave Transform
Person A	1	0.1	3.16	5	2.5	7.07
Person B	9	8.1	9.49	5	2.5	7.07
Group Average	**5**	**4.1**	**6.32**	**5**	**2.5**	**7.07**

This strong criticism of the reliability of subjective wellbeing data for use in comparing groups also casts the conclusions of existing studies into doubt. In response to this, several authors have attempted to defend the robustness of the existing literature and to put forward alternative methods of analysis for future research using subjective wellbeing data. Chen et al. (2019) suggest focusing on the median instead of the mean when analysing subjective wellbeing data, due to the robustness of the median to monotonic rank preserving transformations. Similarly, they also suggest using the equality of mean and median in symmetric distributions to reinterpret existing ordered logit and probit models as median,

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[11] See Bond & Lang (2014) for an intuitive explanation and further examples. Here, we use σ=0.5 and σ =2.

rather than mean, regressions. This reinterpretation makes the conclusions of many existing papers robust to the criticism of Bond and Lang (Chen et al., 2019).

An alternative approach is taken by Bloem (2018), who suggests using a series of data transformations to check the robustness of results obtained using cardinal models. His research presents two key insights. The first is that passing the theoretical criteria developed by Schröder & Yitzhaki (2017) and Bond & Lang (2019) is not a guarantee of reliable results.[12] While it may be possible there is no monotonic rank preserving transformation that will reverse the sign of an estimated coefficient, this is no guarantee that valid transformations will not substantially change both the size and significance of an estimated coefficient. The second insight is that failing the theoretical criteria does not automatically invalidate the results obtained, if only relatively extreme transformations substantially influence the results (Bloem, 2018). Following on from these two insights, Bloem (2018) suggests applying a series of transformations to the underlying data to check the robustness of results to different underlying cardinalizations. we apply the transformation suggested by Bloem (2018) which ensures the endpoints of the data remain numerically unchanged. The transformation is given by Equation (1):

$$T(Y) = Y_{MAX} * \left(\frac{Y}{Y_{MAX}} \right)^{\sigma} \tag{1}$$

When σ is exactly equal to one, the transformed scale exactly equals the reported scale. This means that the "true" distance between reported values of 1 and 2 is assumed to be the same as the distance between reported values of 9 and 10. For values of σ greater than one, the scale is assumed to be convex. This means that the gap between reported values of 1 and 2 is assumed to be smaller than the gap between reported values of 9 and 10. For values of σ less than one, the scale is assumed to be concave, which implies that the gap between reported values of 1 and 2 is greater than the gap between reported values of 9 and 10. The transformation process is shown in Figure , where the σ=1 line reflects the original reported values:

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[12] This is ignoring other reasons why research might produce unreliable results such as omitted variable bias and self-selection bias. Issues such as these would, of course, result in unreliable results irrespective of the issues relating to subjective wellbeing data discussed by Bloem (2018), Bond & Lang (2019), and Schröder & Yitzhaki (2017).

Figure 1: Transformed Variable Example
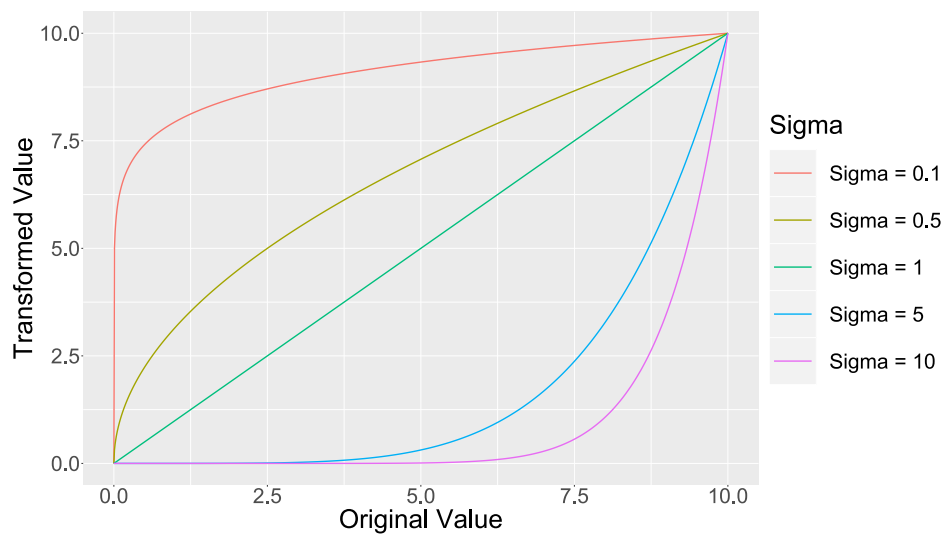
We apply this transformation to all three dependent variables (life satisfaction, recent happiness, and satisfaction with the person's house), using 100 evenly spaced values of σ between 0.1 and 10. Descriptive statistics for a sample of the transformed variables are presented in Table 3. We display the within-person standard deviations as they are the most relevant.[13]

Table 3: Transformed Dependent Variables and Within-Person Standard Deviations (Full Sample)

| Sigma	Life Satisfaction Mean	Life Satisfaction Standard Deviation	Happiness Mean	Happiness Standard Deviation	Satisfaction with House Mean	Satisfaction with House Standard Deviation
0.1	9.74	0.11	5.79	0.09	9.73	0.17
0.5	8.86	0.42	5.08	0.36	8.88	0.58
1	7.94	0.70	4.39	0.57	8.01	0.93
5	4.04	1.36	1.93	0.82	4.59	1.78
10	2.39	1.34	1.05	0.72	3.20	1.88

IV.   Methodology

To examine the impacts of weather-related disaster events on subjective wellbeing we will use a Difference-in-Difference (DiD) estimation approach. The DiD technique can, under

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[13] The within-person standard deviations show how variable an individual's subjective wellbeing is over time.

certain assumptions which we will discuss shortly, generate a causal estimate of a treatment effect.

The simplest version of a DiD analysis consists of two periods of data, with data broken up into a treatment group and a control group. The two groups can be structurally different which means they can have different outcomes in the first period. In the first period, neither group receives a treatment. In the second period, the treatment group receives a treatment while the control group does not. The outcomes of both groups can change. The treatment effect is calculated as the change in the treatment group outcome less the change in the control group outcome[14]. A visual explanation of the DiD technique is presented in Figure 2.

Figure 2: Difference-in-difference Estimation Technique (Columbia Public Health, n.d.).
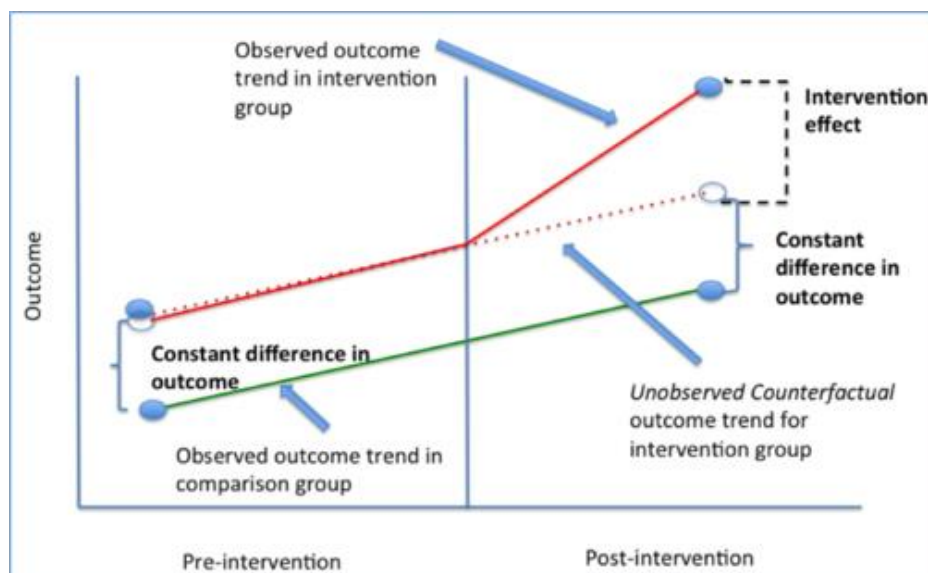
While the DiD technique is quite flexible, it does require several assumptions on the underlying data generating process in order for causal estimates to be obtained. In addition to the assumptions of the ordinary least squares (OLS) technique, four additional assumptions are required for a DiD approach to be valid: the exogeneity assumption, the no pre-treatment effect assumption, the stable unit treatment value assumption (SUTVA), and the common trends assumption (Lechner, 2010).[15] If these four assumptions are met by the underlying data generating process, the DiD estimator will result in causal estimates.

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[14] A key underlying assumption is that, in the absence of no treatment, the treatment group would have experienced the same change as the control group. This is known as the common trends assumption.
[15] Different authors explain these assumptions in subtly different ways. See Columbia Public Health, n.d. for an alternative explanation of the DiD assumptions.

The exogeneity assumption states that the covariates, or control variables, must be independent of the treatment status (Lechner, 2010).[16] It is easy to see why this must be the case. Consider the relationships between happiness, weather-related house damage and income, where weather-related house damage is the dependent variable and income is a covariate. It might seem reasonable to include income as a control variable in the regression, as it would be expected to influence happiness. Unfortunately, this would violate the exogeneity assumption. Experiencing weather-related house damage may be reasonably expected to change income, resulting in endogeneity and invalid estimates. For this reason, only control variables which cannot be influenced by the treatment status may be included in a DiD regression. Clearly, fixed effects based variables pass this criterion, as does the respondent's age. However, we do not believe that any other time-variant variable can be reasonably assumed to be independent of the treatment status. For this reason, we only control for age,[17] as well as both individual and time fixed effects.

The no pre-treatment effect assumption states that the treatment must have no effect in the pre-treatment period (Lechner, 2010). While this may appear trivially true, it is not actually the case in some situation. Primarily, this assumption is violated whenever a person can anticipate treatment or is aware of how they can change their treatment status. We view it as unlikely that this assumption poses a major issue in this analysis, as it would involve people being aware when they were going to suffer weather-related house damage and pre-emptively changing their happiness to reflect this.

SUTVA states that an individual's outcome must only be affected by their individual treatment status, and not by the treatment status of others around them. SUTVA is satisfied if there are no spillover or interaction effects between individuals (Lechner, 2010). Two potential violations of SUTVA exist in this analysis. Firstly, it is possible that people's happiness partially depends on the happiness of people they know. This is intuitively a very reasonable proposition – it seems likely that your happiness may be influenced by the happiness of your family, friends, or neighbours. Secondly, utility may be affected by relative quantity rather

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[16] As per the standard OLS assumptions, the covariates must also be independent of the outcome variable to avoid the classic endogeneity issue. The DiD exogeneity assumption is just an extension of this idea. Including covariates which are endogenous to the treatment status will cause the treatment effect to be "soaked up" by the covariates, resulting in an invalid estimate of the treatment effect.
[17] We include control variables for both age and age squared to capture any non-linearities in the relationship between age and wellbeing.

than absolute quantity. This would result in a person being affected by the treatment that other people receive. Suppose your house was not damaged, however the houses across the road were damaged by a weather-related disaster.[18] The impact of this on your happiness is unclear. Your happiness may go down, with the intuition being you care about those around you and thus you become less happy when they experience material loss due to a weather-related disaster. Your happiness may remain unchanged, as you have personally suffered no loss or no gain. Alternatively, your happiness could increase. The charitable explanation of this would be you feel lucky to emerge unscathed. A considerably less charitable explanation is that you are now considerably better off relative to those who experienced damage, and that has increased your happiness. Both happiness interdependence and the influence of spillover treatment effects would violate SUTVA. The sign and size of these issues are unclear; however, they seem unlikely to be overly large in comparison to the main effect (of experiencing weather-related house damage yourself).

The common trends assumption is widely considered to be the most important DiD assumption (Angrist & Pischke, 2008; Friedman et al., 2013). For the common trends assumption to be satisfied, the difference in pre-treatment outcomes between the treatment and control group must remain constant over the time period where treatment occurs. This key assumption is not testable, as the required counterfactual (the outcomes of the treated group had no treatment occurred) is clearly not observable. However, when a researcher has several time periods worth of data available, he or she can check whether the treatment and control groups have common trends in the periods where treatment does not occur using placebo regressions (Lechner, 2010). While this does not ensure the common trends assumption is met, it can provide the researcher with a degree of confidence around the likely validity of the assumption. Of course, the researcher should also consider whether the treatment coincides with any other shock which is likely to violate the common trends assumption. We view that as unlikely to be the case here, as the treatment (experiencing

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[18] Here we are making the unrealistic assumption that the people who were affected by a weather-related house damage experienced no loss of happiness in order to highlight the possibility of relative happiness effects. This means any change in happiness among the control group must solely be due to relative quantities, and not due to the interdependence of happiness (which is the first potential SUTVA violation we discussed above).

weather-related house damage) is "messy" with different people experiencing treatment in different years.[19]

The best control group is arguably the group of "ever effected" people who did not experience treatment in any given particular year. Allowing for some selection into treatment,[20] this control group has the strongest theoretical grounds for being otherwise identical to the treatment group (the "ever effected" people who did experience treatment in any given particular year). However, for the same reason[21], this control group is also the most likely to experience the SUTVA violations of happiness interdependence and spillover treatment effects. For this reason, we conduct a common trends placebo test on both the "ever affected" control group and the full sample control group, regressing life satisfaction on a dummy variable which takes the value of one the year before weather-related house damage is experienced.[22] Results are nearly identical for both samples. At the original scale, where $\sigma=1$, neither placebo regression is significant at the 5% level suggesting subjective well-being the year before the house damage is not significantly different from subjective well-being the years before that. The full sample placebo becomes significant at the 5% level when $\sigma=0.1$ or $\sigma=3.4$, while the "ever affected" sample placebo reaches 5% significance at $\sigma=4$. These are fairly extreme values of σ. Results of the placebo treatment regression are presented in Figure . Overall, we view it as likely that the common trends assumption holds. In addition, we see no strong theoretical argument why the common trends assumption should not hold given the unpredictable nature of extreme weather events.

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[19] If all treatment occurred over a very short space of time, it increases the possibility that there could be a correlation with another sudden event, such as an unrelated policy change, which may cause the outcomes of the treatment and control groups to diverge irrespective of treatment. This would clearly violate the common trends assumption.

[20] It seems reasonable to assume that certain locations have a higher weather-related disaster risk, meaning that there is some element of selection into treatment status by location selection.

[21] It seems a reasonable assumption that a higher degree of similarity between the treatment and control group will increase the importance of comparisons between the two groups.

[22] This is just a lead of the weather-related house damage (WRHD) variable. This regression also includes dummies for contemporaneous and lags of the weather-related house damage variable, hence the lead dummy compares subjective well-being in the year just before the WRHD to the subjective well-being in the years before that.

Figure 3: Placebo Regression for Full Sample and "Ever Affected" Subsample
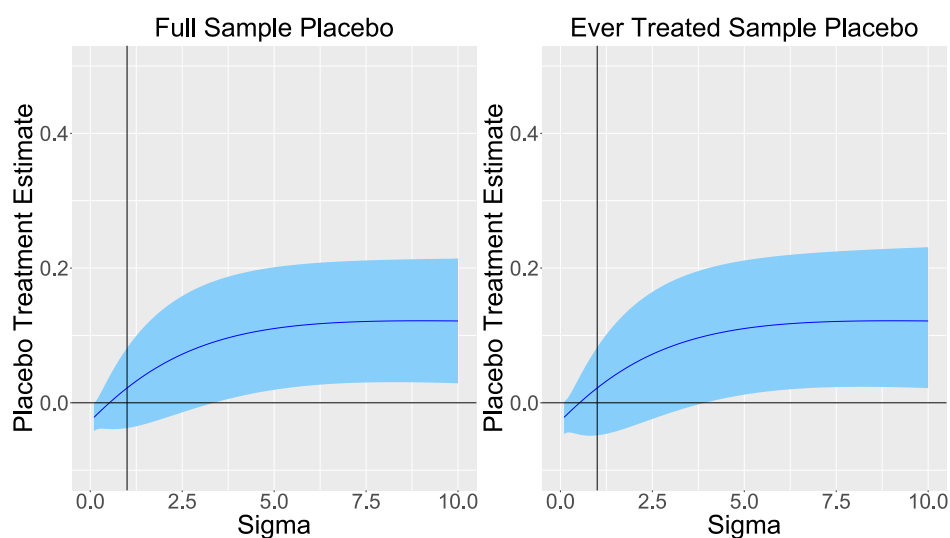
Summarizing, there are three important considerations when deciding upon an estimation strategy. Firstly, it remains unclear to what extent different subjective wellbeing variables measure individual elements of wellbeing as compared to measuring overall wellbeing. A common example of this is the distinction between happiness and life satisfaction. In the dataset we use, there is some evidence to suggest they do measure different things with relatively low correlations between the two variables. The average within-year correlation of life satisfaction and happiness is 0.47, while the average within-person correlation is only 0.20. The second consideration is that the effect of an event on subjective wellbeing may be heterogeneous, with different groups being affected by treatment differently. This includes the possibility of heterogeneity arising for selection into treatment,[23] which could result in the "ever treated" group being structurally different[24] from the "never treated" group. Finally, it is problematic to treat subjective wellbeing data as cardinal for the purposes of analysis (which is commonly done) given almost all authors agree that subjective wellbeing data is ordinal in nature. As shown by Bond & Lang (2019), this can lead to misleading results which are fragile to monotone transformations of the underlying subjective wellbeing data.[25]

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[23] It seems reasonable to assume that certain locations have a higher risk of experiencing a weather-related event and that people are aware of this.
[24] This difference may be unobservable.
[25] These transformations represent different assumed cardinal scales, as we discussed above.

We employ three techniques in our estimation strategy to mitigate these issues and provide more robust estimates. Firstly, we use three different dependent variables in our analysis: life satisfaction (LifeSat), satisfaction with housing (HouseSat),[26] and happiness (Happiness).[27] The use of both life satisfaction and happiness reduces the risk of a misleading result arising from measuring a subset of subjective wellbeing rather than overall subjective wellbeing. We also include satisfaction with housing as it is likely to be the most sensitive to experiencing weather-related house damage.[28] Secondly, we run the analysis upon both the entire sample and three different subsets. These subsets are based on treatment status, homeownership status, and self-reported prosperity level. This allows for the introduction of heterogeneous treatment effects. Finally, we employ a series of data transformations as suggested by Bloem (2018) in order to at least partially mitigate the concerns raised by Bond & Lang (2019).

The model specifications we employ include control variables for age and age squared,[29] as well as both individual and time fixed effects. In addition, all models are run using individual-cluster and time-cluster robust standard errors.[30]

V.   Results

a. Weather Related House Damage on Subjective Wellbeing

In this section we present the regression estimates on the effects of weather-related house damage (WeatherDamage) on subjective wellbeing (SWB) for both the full sample and the "ever treated" subsample. Equation (2) presents the main model specification, where the measure of SWB is alternatively LifeSat(isfaction), HouseSat(isfaction), or Happiness. Individual and time fixed effects are denoted by α_i and t_t respectively.

$$SWB_{it} = \alpha_i + t_t + \beta_1 WeatherDamage1_{it} + \beta_2 WeatherDamage2_{it} + \qquad (2)$$
$$\beta_3 WeatherDamage3+_{it} + \beta_4 age_{it} + \beta_5 age_{it}^2 + u_{it}$$

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[26] This is clearly a subset of overall subjective wellbeing and is not attempting to measure overall subjective wellbeing.

[27] As mentioned earlier, this question asked the respondent how much time they had been happy within the last 4 weeks.

[28] Satisfaction with housing is quite clearly a subset of overall subjective wellbeing.

[29] We do not include additional control variables as explained below.

[30] The standard errors are both individual-cluster robust and time-cluster robust. We obtain these using the R function *vcoc*DC from the package *plm*. See https://www.rdocumentation.org/packages/plm for more details.

We estimate three different treatment effects. Any impact on subjective wellbeing that occurs within 12 months of treatment (Year 1) is captured by the term β_1. Similarly, β_2 is the estimate of any impact between 12- and 24-months following treatment (Year 2). Finally, we allow for a "long run" treatment effect that occurs in all later time periods (Year 3+). Table 4 presents the results obtained from running the model specification in Equation (2).

Table 4: Weather-Related House Damage on Different Measures of Subjective Wellbeing

Year	LifeSat		HouseSat		Happiness	
	Full	Ever	Full	Ever	Full	Ever
1	-0.03	-0.04	-0.06	-0.08*	-0.03**	-0.02
2	-0.08***	-0.09***	-0.03	-0.05	-0.01	-0.01
3+	-0.02	-0.06	0.07*	0.03	-0.02	-0.01

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

Experiencing weather-related house damage is associated with a small but statistically significant decrease in life satisfaction in the 12-24-month period (Year 2) after the weather event occurs. For the full sample, we estimate life satisfaction decreases by 0.08 points. For the "ever affected" sample, we estimate life satisfaction decreased by 0.09 points. Both estimates are statistically significant at the 1% level. Otherwise, we estimate results which are generally insignificant with no other estimated coefficient significant at the 1% level. When using house satisfaction as the dependent variable, not a single estimated coefficient is significant at the 5% level, and only two estimate coefficients are significant at the 10% level. When using happiness as the dependent variable, only a single coefficient is significant at either the 5% or the 10% level. Finally, there is no clear systemic difference between estimates obtained when using the full sample and those obtained when using the "ever treated" subsample.

While the results are generally insignificant, it should be noted that the estimates are almost always negative. Still, magnitudes of all 18 estimated coefficients are small relative to the mean and variance[31] of the respective variables. These are presented in Table 5 below. Table

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[31] Here we refer to the within-person variance. When considering how small or large the estimated treatment effect is, what matters is not the variance of wellbeing across people, but how variable an individual's wellbeing is over time.

6 presents the coefficient estimates as a percentage of the average within-person standard deviation.

Table 5: Mean and Standard Deviation of Subjective Wellbeing Measures

	Full Sample		Ever Treated Sample	
	Mean	Standard Deviation	Mean	Standard Deviation
LifeSat	7.94	0.70	7.84	0.84
HouseSat	8.01	0.93	7.91	1.13
Happiness	4.39	0.57	4.30	0.66

Table 6: Effect of Experiencing a Weather-Related Natural Disaster as a Percentage of Within-Person Standard Deviation of Subjective Wellbeing

Year	LifeSat		HouseSat		Happiness	
	Full	Ever	Full	Ever	Full	Ever
1	3.96%	4.93%	6.91%	7.12%*	5.37%**	3.75%
2	11.06%***	11.20%***	3.55%	4.28%	1.90%	0.98%
3+	3.35%	6.98%	7.14%*	2.91%	4.28%	2.01%

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

The largest impacts on both life satisfaction occur in the year following experiencing weather-related house damage, while happiness is generally more affected in the year of treatment. The overall estimated effect is fairly small, with no treatment coefficient explaining over 11.2% of the within-person standard deviation on subjective wellbeing.

We now carry out a robustness check of our main model estimates by applying the data transformation suggested by Bloem (2018). It is important to note that any such transformation will affect both the mean and the distribution of the data and thus the resulting coefficient estimates and p-values. Section 3 provides an overview of how the mean and within-person standard deviation change when the transformation is applied. We present the regression results of the transformed data below. The full sample and "ever affected" sample estimates of weather-related house damage on life satisfaction are displayed in Figure 4 and Figure 5. The full sample and "ever affected" sample estimates of weather-related house damage on satisfaction with housing are displayed in Figure 6 and Figure 7. Finally, the full sample and "ever affected" sample estimates of weather-related house damage on happiness are displayed in Figure 8 and Figure 9. All figures display both the point estimate and the 95% double-cluster robust confidence interval.

In general, the estimates are all robust to transformations of the assumed underling cardinal scale and the assumption of a different scale would not change the conclusions drawn above. Interestingly, the Year 2 estimate of weather damage on life satisfaction is moderately fragile to the transformation. The full sample estimate becomes insignificant at the 1% level at σ=1.8 and insignificant at the 5% level at σ=3.1. The "ever affected" sample estimate becomes insignificant at the 1% level at σ=2.7 and insignificant at the 5% level at σ=3.9. These are not unreasonable transformations. A σ value of 1.8 implies that that a person who reports a wellbeing score of 10 has about 3.5 times the wellbeing as someone who reports a score of 5, rather than double the wellbeing as the untransformed cardinal scale would imply. A σ value of 2.7 implies this difference is about 6.5 times. Other estimates either remain statistically insignificant or rapidly lose significance. For example, the Year 1 full sample estimate of weather damage on happiness loses 5% significance at σ=1.1 and loses 1% significance at σ=1.9.

Overall, while the effect of weather damage on life satisfaction is statistically significant, it is fairly small in magnitude. The estimates of weather damage on satisfaction with housing and happiness are generally both statistically insignificant and small in magnitude. Applying the data transformation generally makes results less statistically significant, with the estimates of weather damage on life satisfaction losing 1% significance at fairly moderate transformations.

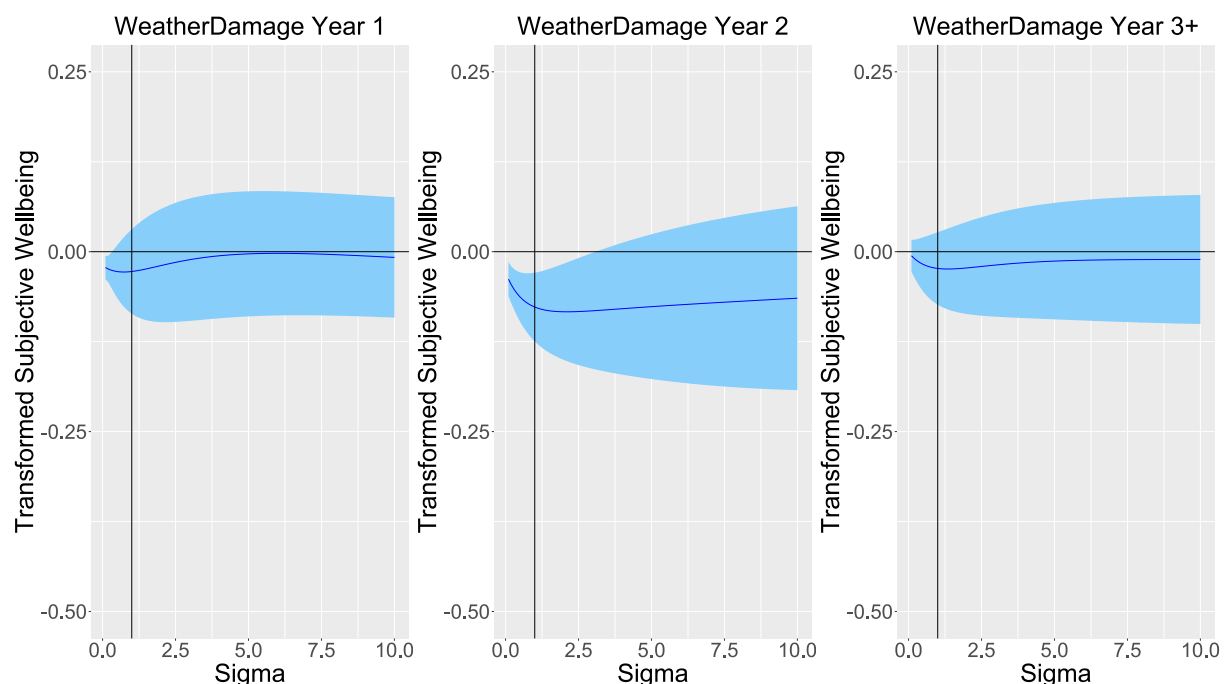Figure 4: Weather-Related House Damage on Transformed Life Satisfaction (Full Sample)

Figure 5: Weather-Related House Damage on Transformed Life Satisfaction (Ever Affected Sample)
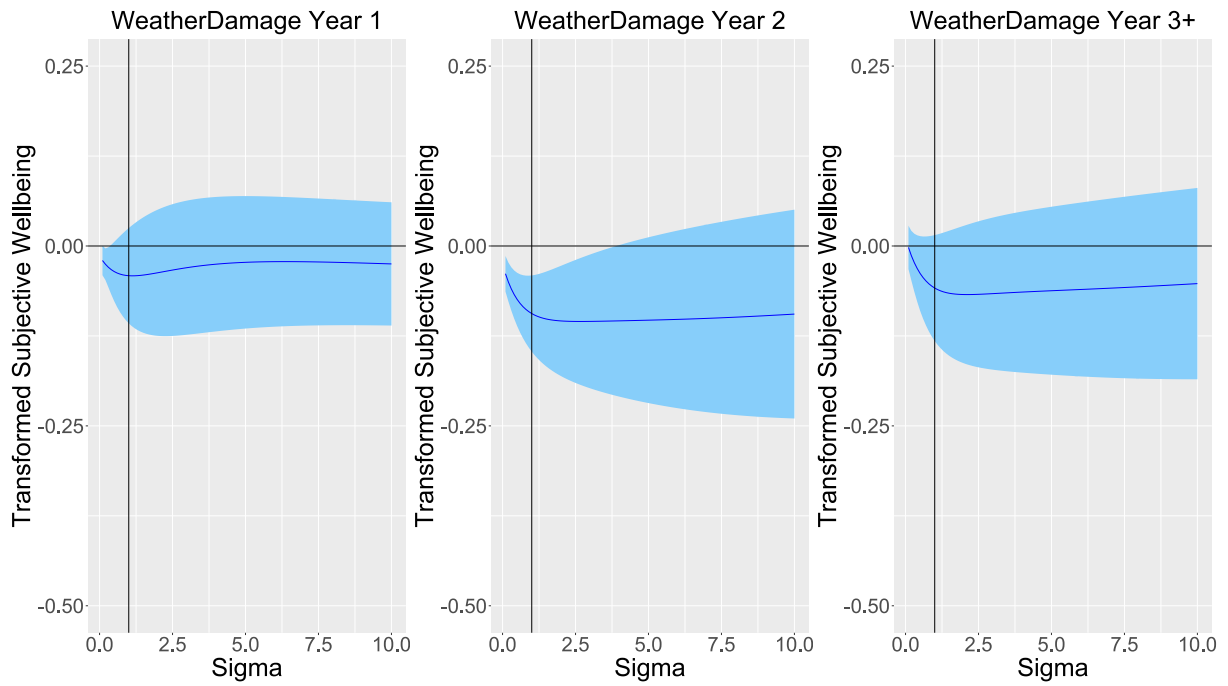

Figure 6: Weather-Related House Damage on Transformed Satisfaction with Housing (Full Sample)
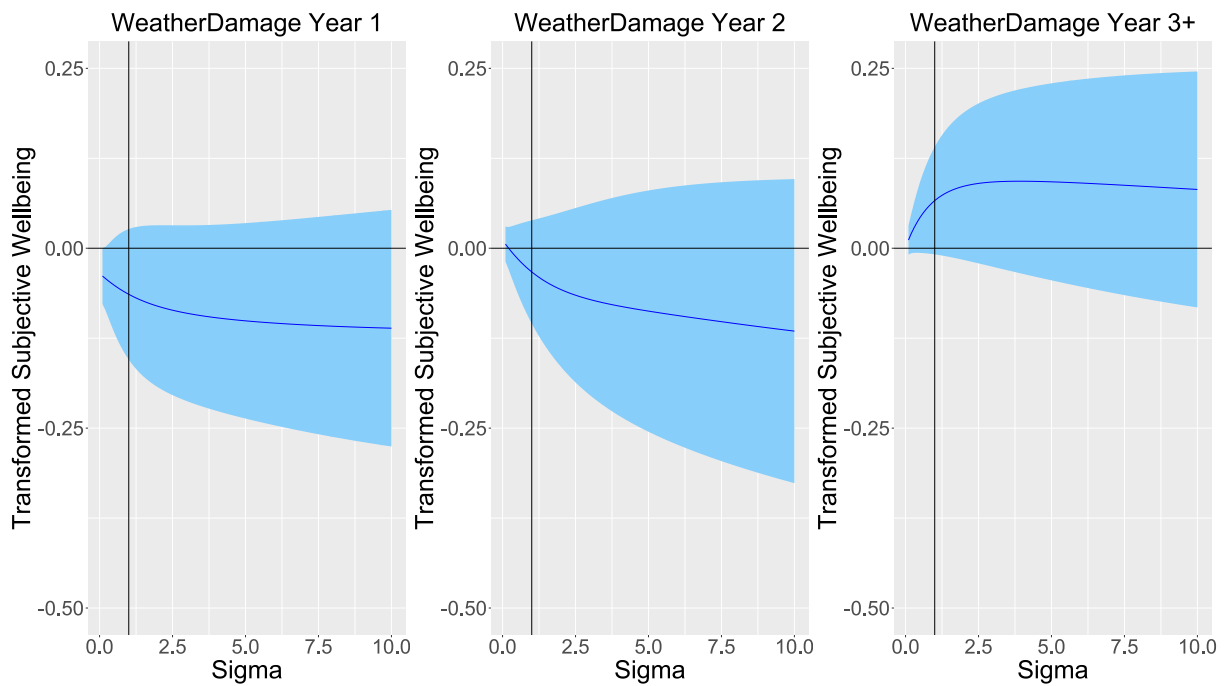
Figure 7: Weather-Related House Damage on Transformed Satisfaction with Housing (Ever Affected Sample)
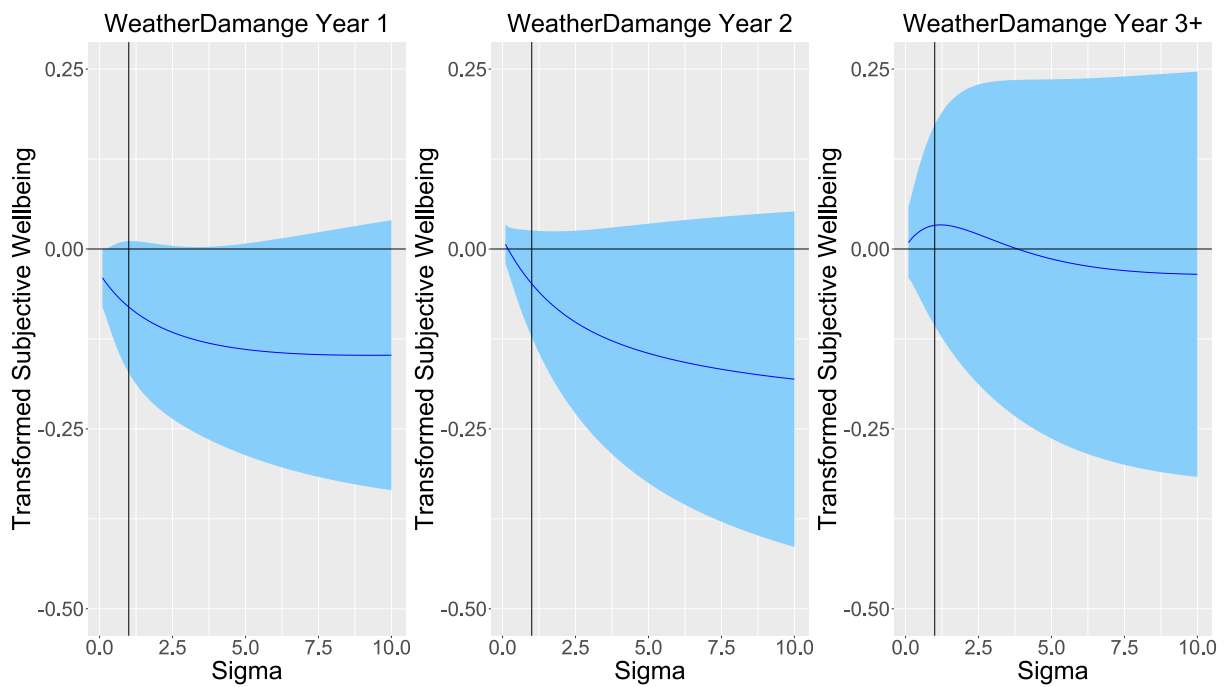

Figure 8: Weather-Related House Damage on Transformed Happiness (Full Sample)
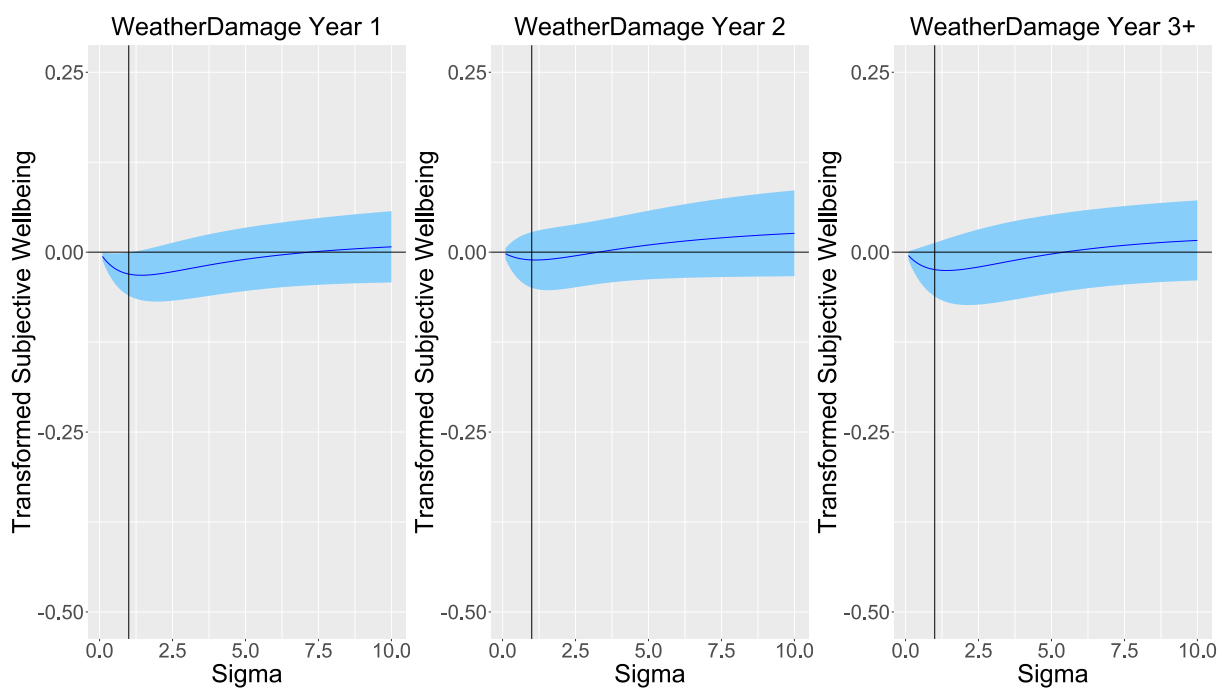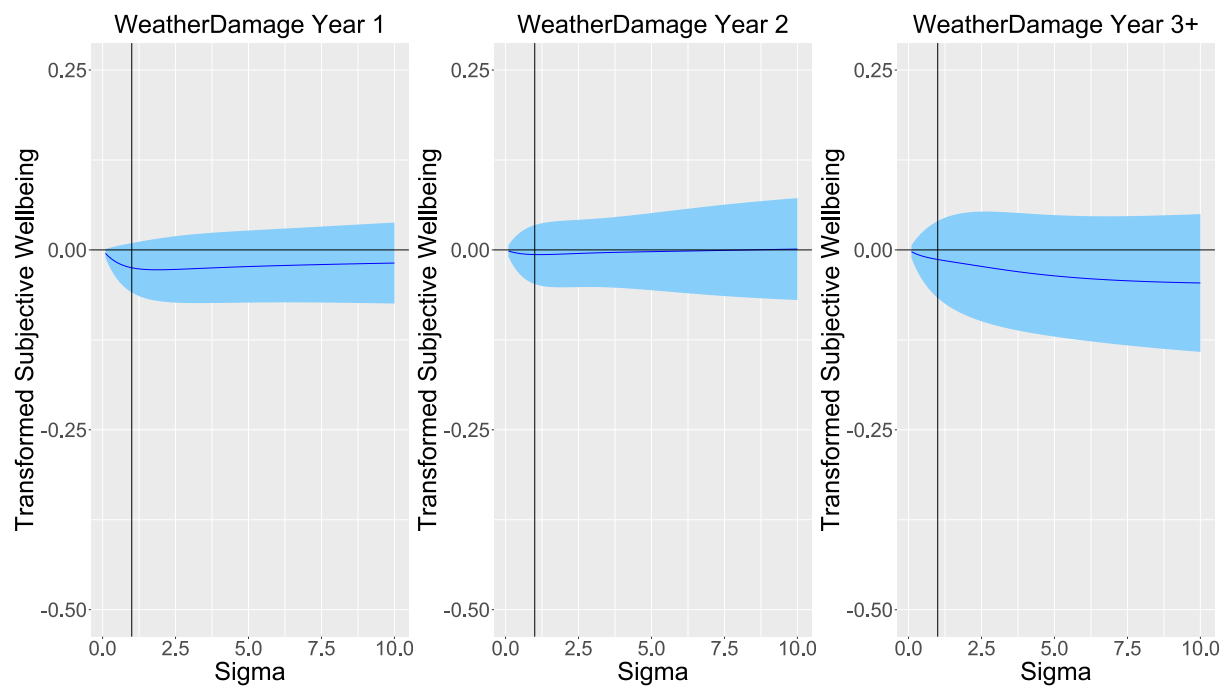
Figure 9: Weather-Related House Damage on Transformed Happiness (Ever Affected Sample)

b. Major Life Events on Subjective Wellbeing

We showed so far that experiencing weather-related house damage results in relatively small and mostly insignificant effects on subjective wellbeing, whether measured by life satisfaction or happiness. The question naturally arises as to whether any life event affects subjective wellbeing, or whether the majority of variance in subjective wellbeing is essentially random in nature. In this section we compare the effect from experiencing weather-related house damage (WeatherDamage) on subjective wellbeing to the effects from experiencing either long-term relationship breakup (Separation) or involuntary loss of job (JobLoss)[32] on subjective wellbeing. As before, results are presented for both the full sample and the "ever treated" subsample (all those who have ever experienced weather-related house damage), and we use both group and time cluster-robust standard errors. Equation (3) presents the main model specification, where *EVENT* is alternatively Separation, JobLoss, or WeatherDamage.[33]

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[32] An involuntary loss of job includes both being fired and being made redundant.

[33] The random element in weather related house damage is likely to be bigger than the random element in job loss and separation. Hence, the estimates of the impact of weather related damage are more likely to be unbiased than the estimates of the impact of job loss and of separation. A priori, it's hard to say, however, in what direction the bias would be.

$$LifeSat_{it} = \alpha_i + t_t + \beta_1 EVENT1_{it} + \beta_2 EVENT2_{it} + \beta_3 EVENT3+_{it}$$
$$+\beta_4 age_{it} + \beta_5 age_{it}^2 + u_{it} \qquad (3)$$

The interpretation of all coefficients is the same as for Equation (2). The results from estimating Equation (3) are presented below. Here, the full sample is almost certainly the better comparison group, as any heterogeneity arising from selection into treatment[34] seems unlikely to affect how the individual would respond to a different life event. Additionally, the use of the "ever treated" sample results in a significant reduction of the number of observations. In the full sample of 144,784 observations, there are 5,033 instances of a long-term relationship breakup and 4,320 instances of an involuntary loss of job. In the "ever affected" sample of 13,809 observations, there are only 524 instances of a long-term relationship breakup and 544 instances of an involuntary loss of job. The "ever affected" sample results are thus presented mainly for consistency. However, on the whole they are fairly similar to the full sample estimates.

i. Major Life Events on Life Satisfaction

In this section we present the estimates of major life events on life satisfaction. Table 7 presents the coefficient estimates, while Table 8 presents the estimates as a percentage of within-person standard deviation.

Table 7: Major Life Events on Life Satisfaction

Year	WeatherDamage		Separation		JobLoss	
	Full	Ever	Full	Ever	Full	Ever
1	-0.03	-0.04	-0.34***	-0.39***	-0.15***	-0.24***
2	-0.08***	-0.09***	-0.08***	-0.03	-0.05***	-0.08
3+	-0.02	-0.06	0.04*	-0.01	0.01	-0.12

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

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[34] A treated unit is one who experiences weather-related house damage.

Table 8: Major Life Events as a Percentage of Within-Person Standard Deviation of Life Satisfaction

Year	WeatherDamage		Separation		JobLoss	
	Full	Ever	Full	Ever	Full	Ever
1	3.96%	4.93%	48.24%***	47.02%***	21.57%***	28.28%***
2	11.06%***	11.20%***	11.75%***	3.89%	7.10%***	9.30%
3+	3.35%	6.98%	5.87%*	1.64%	1.47%	14.58%

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

For the full sample, the Year 1 effect from experiencing a long-term relationship breakup is an 0.34-point reduction in life satisfaction, which corresponds to 48% of a within-person standard deviation. The Year 2 effect is an 0.08-point reduction, or 11% of a within-person standard deviation. Year 3+ effects are insignificant at the 5% level. For the "ever treated" sample, the estimates are similar. The Year 1 effect is an 0.39-point reduction in life satisfaction, which corresponds to 47% of a within-person standard deviation. Year 2 and Year 3+ effects are statistically insignificant.

The effect of involuntary loss of job is less severe, but still significant and large in magnitude. For the full sample, the Year 1 effect is an 0.15-point reduction in life satisfaction, while the Year 2 effect is an 0.05-point reduction. These estimates correspond to 21% and 7% of a within-person standard deviation. Year 3+ effects are again insignificant. For the "ever treated" sample results are also generally similar. The Year 1 effect is an 0.24-point reduction in life satisfaction, which is 28% of a within-person standard deviation. Year 2 and Year 3+ effects are statistically insignificant.

Overall, experiencing weather-related house damage only has a small effect on life satisfaction. Weather-related house damage is never estimated to explain more than 11.2% of a within-person standard deviation. In contrast, both separation and job loss have much larger effects on life satisfaction. In particular, The Year 1 effect of experiencing separation is estimated to be over 45% of a within-person standard deviation for both the full sample and "ever treated" group. The Year 1 effect of experiencing job loss is estimated to be over 21%

of a within-person standard deviation for both the full sample and "ever treated" subsample.[35]

ii. Major Life Events on Happiness

In this section we present the estimates of major life events on happiness. Table 9 presents the coefficient estimates, while Table 10 presents the estimates as a percentage of within-person standard deviation.

Table 9: Major Life Events on Happiness

Year	WeatherDamage		Separation		JobLoss	
	Full	Ever	Full	Ever	Full	Ever
1	-0.03**	-0.02	-0.16***	-0.05	-0.07***	-0.08**
2	-0.01	-0.01	0.00	-0.02	-0.03	-0.09
3+	-0.02	-0.01	0.07	0.10*	-0.02*	-0.11***

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

Table 10: Major Life Events as a Percentage of Within-Person Standard Deviation of Happiness

Year	WeatherDamage		Separation		JobLoss	
	Full	Ever	Full	Ever	Full	Ever
1	5.37%**	3.75%	28.01%***	7.67%	12.47%***	11.82%**
2	1.90%	0.98%	0.87%	3.40%	5.77%	13.25%
3+	4.28%	2.01%	12.76%	15.19%*	3.40%*	15.84%***

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

For the full sample, the Year 1 effect from experiencing a long-term relationship breakup is an 0.16-point reduction in happiness, which corresponds to 28% of a within-person standard deviation. The Year 2 and Year3+ effects are statistically insignificant. For the "ever treated" sample, all three coefficient estimates are insignificant at the 5% level. Interestingly, both the full sample and "ever affected" sample have positive Year3+ coefficient estimates which are similar to full sample Year 3+ estimate of separation on life satisfaction. It certainly seems possible that, after a short period of unhappiness arising from the end of a long-term

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[35] These results are generally robust to applying the transformations discussed in section 3. Detailed results are available upon request.

relationship, an individual gains in happiness from having left a relationship where presumably at least one partner was unhappy.[36]

For the full sample, the Year 1 effect from experiencing involuntary loss of job is an 0.07-point reduction (significant at the 1% level), which corresponds to 12.47% of a within-person standard deviation. Year 2 and Year3+ effects are insignificant at the 5% level. For the "ever affected" sample, the Year 1 effect is an 0.08-point reduction (significant at the 5% level), which corresponds to 11.82% of a within-person standard deviation. The Year 2 effect is insignificant. Interestingly, the Year 3+ effect is an 0.11-point reduction (significant at the 1% level). Irrespective of whether looking at the full sample or the "ever treated" subsample, the estimated effects on happiness from experiencing either a relationship breakup or involuntary loss of job are almost always larger than those of experiencing weather-related house damage.

Overall, the effect on happiness is similar, although often slightly smaller in magnitude, to the effect on life satisfaction. Weather-related house damage has small (no more than 6% of a within-person standard deviation) and insignificant effects, while both separation and involuntary job loss have larger and more significant effects. As found earlier, a long-term relationship breakup has the largest impact on happiness (28% of a within-person standard deviation for the full sample). Also, as earlier, the "ever treated" sample seems to be more negatively impacted by involuntary job loss than the full sample, especially in the long term.[37,38]

iii. Major Life Events on Satisfaction with Housing

In this section we present the estimates of major life events on satisfaction with housing. Table 11 presents the coefficient estimates, while Table 12 presents the estimates as a percentage of within-person standard deviation.

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[36] There is unfortunately no way to ascertain whether the individual was the person choosing to end the relationship or not.

[37] Significance levels are once again mixed.

[38] The conclusions drawn are mostly robust to the transformation described in section 3, though it should be noted that the full sample Year 1 estimate of involuntary job loss is moderately fragile to this transformation. At $\sigma=5.2$, it becomes insignificant at the 1% level, and by $\sigma=7.5$ it becomes insignificant even at the 10% level. However, these are fairly extreme transformations.

Table 11: Major Life Events on Satisfaction with Housing

Year	WeatherDamage		Separation		JobLoss	
	Full	Ever	Full	Ever	Full	Ever
1	-0.06	-0.08*	-0.20***	-0.25***	0.00	0.00
2	-0.03	-0.05	-0.07*	-0.05	-0.02	-0.06
3+	0.07*	0.03	0.04	0.08	0.00	-0.16**

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

Table 12: Major Life Events as a Percentage of Within-Person Standard Deviation of Satisfaction with Housing

Year	WeatherDamage		Separation		JobLoss	
	Full	Ever	Full	Ever	Full	Ever
1	6.91%	7.12%*	21.97%***	21.80%***	0.43%	0.18%
2	3.55%	4.28%	7.71%*	4.81%	1.93%	5.09%
3+	7.14%*	2.91%	4.44%	7.10%	0.38%	14.53%**

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

As previously discussed, the impact of experiencing weather-related house damage on satisfaction with housing is generally small in both magnitude and significance. For both the full and "ever treated" sample, no estimate is larger than 8% of a within-person standard deviation, and no estimate is significant at even the 5% level. However, the effects of a long-term relationship breakup are both larger in magnitude and statistical significance. For the full sample, the Year 1 estimate is an 0.20-point reduction in house satisfaction (21 % of a within-person standard deviation). It is significant at the 1% level. For the "ever treated" sample, the Year 1 estimate is an 0.25-point reduction in house satisfaction (21% of a within-person standard deviation), which is significant at the 1% level. For both the full sample and the "ever treated" sample, neither the Year2 nor Year 3+ estimates are significant at even the 5% level.

For the full sample, involuntary job loss results in small and insignificant estimates. For the "ever treated" sample, the Year 1 and 2 effects are both insignificant. Interestingly the Year 3+ estimate is fairly large (-0.16 or 14% of a within-person standard deviation) and is significant at the 5% level. This is similar to the previously discussed results where the "ever treated" sample seems to be more negatively affected by loss of job, especially in the long term.

Overall, house satisfaction is relatively unaffected by weather-related house damage. However, it is significantly more affected by either involuntary job loss or separation. While the impact of weather-related house damage is never more than 8% of a within-standard deviation and is never significant at even the 5% level, the estimate on separation is over 20% of a standard deviation and is also more significant (significant at the 1% level). Interestingly, again the impact of involuntary job loss is greater for the "ever treated" sample than for the full sample.[39]

c. Weather Related House Damage on Subjective Wellbeing by Subset

As previously discussed, it is possible that different groups of people experience different subjective wellbeing effects from weather-related house damage. Other studies which use subjective wellbeing have found mixed evidence of the existence of such heterogeneous effects. This is discussed in some detail in Section 2. Here we allow for heterogeneous effects by treatment status and show that the results do not materially change. In this section, we allow for heterogeneous effects by three additional categories: gender, wealth, and homeownership status.

Due to the nature of the "ever treated" sample, all people in it experienced weather-related house damage, and all people who experienced weather-related house damage were in the "ever treated" sample. This is not the case with the subsets based on gender, wealth, or homeownership status. For example, not all homeowners experience weather-related house damage, and not all weather-related house damage is experienced by homeowners. This allows for the inclusion of interaction effects between each variable[40] and the relevant subset, and the ability to test whether the difference between groups is statistically significant. The empirical model is presented in Equation (4).

Below we present the results by wealth status only, as we find no clear differences in impact by gender or by homeownership.[41]

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[39] In general, the results are robust to the data transformations described in section 3.
[40] We interact the time fixed effect with subset but do not interact the individual fixed effect. All other variables are interacted with the relevant subset.
[41] These results are available on request.

$$SWB_{it} = \alpha_i + t_t + \beta_1 WeatherDamage1_{it} + \beta_2 WeatherDamage2_{it} +$$
$$\beta_3 WeatherDamage3+_{it} + \beta_4 age_{it} + \beta_5 age_{it}^2 + \beta_6 Subset_{it} +$$
$$\beta_7 WeatherDamage1_{it}Subset_{it} + \beta_8 WeatherDamage2_{it}Subset_{it} + \quad (4)$$
$$\beta_9 WeatherDamage3 +_{it} Subset_{it} + \beta_{10} age_{it}Subset_{it} + \beta_{11} age_{it}^2 Subset_{it}$$
$$+\beta_{12} t_t Subset_{it} + u_{it}$$

i.

In this section we present the effects of weather-related house damage (WeatherDamage) on subjective wellbeing (SWB) for both the wealthy and the poor. People who we define as wealthy are all those who self-reported as being at least "Reasonably Comfortable", while those who we define as poor reported being either "Just Getting Along" or worse. Coefficient estimates are presented in Table 13, while coefficient estimates as a percentage of a within-person standard deviation are presented in Table 14. Differences in the coefficient estimates are presented in Table5.

Table 13: Weather-Related House Damage on Subjective Wellbeing by Wealth

Year	LifeSat		HouseSat		Happiness	
	Wealthy	Poor	Wealthy	Poor	Wealthy	Poor
1	0.02	-0.11*	-0.03	-0.11**	-0.02	-0.05*
2	-0.03	-0.13**	0.02	-0.10	0.01	-0.04
3+	0.03	-0.10**	0.10**	0.02	-0.00	-0.05

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

Table14: Weather-Related House Damage as a Percentage of a Within-Person Standard Deviation by Wealth

Year	LifeSat		HouseSat		Happiness	
	Wealthy	Poor	Wealthy	Poor	Wealthy	Poor
1	4.42%	17.82%*	4.25%	13.31%**	3.20%	11.43%*
2	5.90%	22.01%**	2.03%	12.15%	2.10%	8.44%
3+	4.49%	15.63%**	12.65%**	2.18%	0.70%	10.91%

Note: * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$

Table15: Differences in Weather-Related House Damage on Subject Wellbeing by Wealth Status (Wealthy - Poor)

Year	LifeSat	HouseSat	Happiness
1	0.13**	0.08	0.04

2	0.10	0.12	0.05
3+	0.12***	0.08	0.05

Note: * p < 0.1; ** p < 0.05, *** p < 0.01

For the wealthy, coefficient estimates are almost always small in size and statistically insignificant. The largest and most statistically significant coefficient estimate is the Year 3+ estimate on house satisfaction, which is 0.1 or 12.65% of a within person standard deviation, and statistically significant at the 5% level. Interestingly, this estimate is positive, as are five of the other eight coefficient estimates for the wealthy. However, no other coefficient estimate is statistically significant at even the 10% level. In general, the wealthy do not experience any loss of wellbeing from a weather-related disaster and may even experience a small gain.

In contrast, the poor appear significantly more impacted from suffering weather-related house damage, with estimates coefficient generally larger and more statistically significant. While no estimated coefficient is significant at the 1% level, three are significant at the 5% level and an additional two are significant at the 10% level. The estimates on life satisfaction are generally the largest, with the Year 2 estimate being over 22% of a within-person standard deviation, and the long term Year3+ estimate being over 15.5% of a within-person standard deviation. The Year 1 estimate is significant at the 10% level or greater irrespective of which measure of subjective wellbeing is chosen and is always greater than 11.4% of a within-person standard deviation.

The differences between wealthy and poor are statistically significant for the Year 1 (5% level) and Year 3+ (1% level) coefficient estimates of weather-related house damage on life satisfaction. Overall, the wealthy are relatively unaffected by weather-related house damage. However, the poor appear to suffer a large and statistically significant decline in subjective wellbeing following weather-related house damage. In the case of life satisfaction, this drop appears to be long lasting, with the poor experiencing no return to pre-disaster levels of life satisfaction.

VI.   Discussion

We have found little evidence to suggest weather-related house damage leads, on average, to a significant decline in subjective wellbeing. We show that there is evidence of a statistically

significant (at the 1% level) decline in life satisfaction in the 12-24-month period following weather-related house damage, however this decline is limited in size, explaining less than 11.21% of a within-person standard deviation. In addition, it is not robust to alternative measures of subjective wellbeing, with neither happiness nor house satisfaction showing any statistically significant effect over this period. Other estimated coefficients are both smaller and less statistically significant, and this conclusion is robust to the use of either the full sample or the "ever affected" sample. We find that men and women, and homeowners and non-homeowners, are similarly affected by weather-related house damage with estimates being small in size, frequently statistically insignificant, and not robust to alternative measures of wellbeing. An exception to this is the case of people who are poor. We find that when poorer people are affected by weather-related house damage, they experience a substantial, statistically significant, and long-lasting decline in life satisfaction.[42] But this finding is the exception: in general, subjective wellbeing was not significantly affected by weather-related house damage. This might seem like a surprising result at first glance, especially given the insignificant effect from experiencing weather damage extends not just to life satisfaction and happiness but also to satisfaction with housing.

In contrast, we find that either separation or job loss is associated with a decline in subjective wellbeing that is larger in size, more statistically significant, and more robust to different measures in subjective wellbeing. Coefficient estimates are as large as 48.24% of a within-person standard deviation for separation and 28.28% of a within-person standard deviation for loss of job. Interestingly, we estimate a substantial long-term decline in wellbeing following job loss for the "ever affected" sample[43] but not for the full sample. The long-term estimate is never less than 14.5% of a within-person standard deviation for the "ever affected" sample, but never greater than 3.41% of a within-person standard deviation for the full sample. This difference in wellbeing impact of job loss may be due to locational differences, with the "ever affected" perhaps more likely to live in rural locations where there are fewer employment opportunities.[44]

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[42] With house satisfaction and happiness also being affected however less significantly so than life satisfaction.
[43] The "ever affected" sample are all those who ever experienced weather-related house damage.
[44] This is selection into treatment, which we discuss further in the context of weather-related house damage.

There are several plausible explanations for why we do not find a material impact of weather-related house damage on subjective wellbeing. Of course, the first is that most people's wellbeing is simply unaffected by experiencing weather-related natural disasters, and therefore a null result is almost guaranteed. However, there are several alternative explanations which may also explain why we find a null result.

One possibility for the null result is that there is selection into treatment status by size of treatment effect. Assuming certain locations are more prone to weather-related disasters, it is a reasonable expectation these disaster-prone locations primarily contain people who are relatively less affected by said disasters than those who choose to live elsewhere. And while disaster-averse wealthy could choose to live in less disaster-prone locations, the especially disaster-averse poor may be unable to afford to do so. Thus, selection into treatment is consistent with both a null result overall as well as with the poor being more negatively impacted than other groups. If there is indeed selection into treatment, the conclusion (of a null result) remains valid providing that weather-related natural disasters remain "predictable" by location and thus allow selection into treatment to continue. If climate change resulted in weather-related natural disasters becoming more randomised so that selection into treatment could no longer occur, the average affect (of weather-related house damage on subjective wellbeing) would be likely to increase.

In addition to selection into treatment, there are several uncontrolled for factors which may also help explain the null result: severity of damage experienced, social comparisons, insurance coverage, and government assistance. First, the null result may be explained by a low average severity of experienced damage.[45] When studying the impacts of weather events on subjective wellbeing in Papua New Guinea, Lohmann et al (2019) found suffering more severe damage resulted in a larger loss of wellbeing than suffering moderate damage. Unfortunately, data on the severity of weather-related house damage experienced was not collected as part of the HILDA survey, making this theory untestable. However, it is at least a possibility that the majority of people who experienced weather-related house damage only experienced mild damage, and this dominated in deriving the estimated effect. Interestingly, a fixed dollar value level of damage would appear bigger (in relative terms) for the poor than

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[45] The 2019-2020 "Black Summer" bushfire season was unusually severe however is not included in our dataset due to how recently it occurred.

the wealthy. Thus, even if the majority of experienced damage appeared minor to most people, it may have appeared large to the poor and as a result affected their wellbeing more than other groups.

Social comparisons may also help explain the null result. It is widely accepted in the wellbeing literature that wellbeing may depend just as much upon relative factors as upon absolute factors. This social channel may lead to the null result found. Firstly, weather disasters are naturally clustered. A given disaster will be confined geographically. Thus, people affected by a weather disaster are almost certain to know other people affected by a weather disaster. If comparisons are strongly localised, people may adapt quickly to a weather disaster because everyone around them is also affected. In reality, this is related to the conclusion drawn by Calvo et al., (2015) who found social connectedness played an important role in wellbeing recovery following Hurricane Katrina, with the socially isolated experiencing a long term drop in wellbeing. This possible reason is also consistent with the greatest impact being on the poor. The poor might be less well-equipped to cope with short-term needs which may arise following a disaster.[46] They may thus not only experience a decline in their welfare due to the direct effect of disaster itself, but also a decline in their relative welfare due to the better ability of other, wealthier, people to respond to a disaster.

Insurance coverage may also help explain the lack of any significant impact on wellbeing. Australia is a wealthy developed country with a functioning insurance market. Using European data over a 25-year time span, Luechinger & Raschky (2009) found that while experiencing a weather-related disaster did have a negative effect on wellbeing, this was mostly mitigated by the presence of risk-transfer mechanisms. If most people who experienced weather-related house damage had insurance, the reimbursement from their insurance companies may explain the relative lack of any effect on wellbeing. Unfortunately, there is very limited data collected on insurance as part of HILDA. Data on whether respondents had home contents insurance was only collected in two years: 2014 and 2018. However, this does provide enough data to comment on the distribution of home contents insurance. Overall, 78% of respondents held home contents insurance during the two years where data is

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[46] A relatively free supply of money can be expected to reduce frictions which may arise following a weather-related disaster, whether it be by allowing damaged goods to be quickly replaced, being able to physically move away from the affected location, or other choices which increase a person's wellbeing following an adverse event.

available. However, we view it as unlikely that home contents insurance coverage (or lack thereof) plays too large a role in explaining the null result. While the overall average is certainly high, it is also highly uneven. Almost 84% of the wealthy held home contents insurance while only just over 65% of the poor did. However, this difference should not be assumed to explain why the poor were the most impacted by a weather disaster given the results contrasting homeowners and non-homeowners. Almost 94% of homeowners held home contents insurance while not even 44% of non-homeowners did. Given this 50-percentage point difference in home contents insurance coverage did not lead to a significant difference in wellbeing, it would be egregious to explain away the difference between the poor and wealthy as being caused by the 19-percentage point difference in home contents insurance coverage.

Finally, the presence of government disaster relief efforts may help explain the null result. The Australian government has numerous disaster relief programmes which provide financial assistance after a disaster. For example, there are both once-off payments and short-term income support payments available for individuals affected by disasters (Portillo-Castro, 2019). As of 2018, it was estimated that the direct cost of these disaster recovery programmes was $2.75 billion per year (Portillo-Castro, 2019). Given that the aim of disaster recovery aid is to minimise the harm caused by a disaster and to aid in the recovery, the null result may be at least partially caused by government disaster relief efforts.

Given the limitations of our particular dataset, it is difficult to know the degree to which each of these four factors help explain the overall null result. However, it certainly seems reasonable that a low average disaster severity, social comparisons, high level of insurance coverage, and government disaster relief efforts all play a role in explaining the null result. Of these four factors, low average disaster severity and social comparisons are also consistent with the poor being more negatively impacted than other groups. Similarly, selection into treatment status by location is also consistent with both a null result and with the poor being more negatively impacted than other groups. It is also not clear whether the impact of future weather-related disasters will be similar to previous ones. Climate change is likely to make extreme weather events increase in both severity and frequency, exposing more people to weather-related house damage and making it harder for selection into treatment to occur. It is worth noting that climate change also has the potential to reduce the availability of

insurance and to reduce the ability of governments to provide post-disaster aid. All these possibilities could reasonably be expected to result in future weather disasters having a larger wellbeing impact than past ones.

At the same time, while one can argue that weather-related natural disasters are something for people and governments to be concerned about, so too one can argue that other life events such as loss of job or relationship breakup are something for people and governments to be concerned about. We find large negative impacts on wellbeing arising from separation of job loss suggesting the Australian government might want to devote more attention to these aspects of people's lives. This is especially the case considering that both job loss and separation occur considerably more frequently than weather-related house damage. While fewer than 1.5% of people experience weather-related house damage in a given year, over 3.2% of people experience job loss and over 3.4% experience separation. Government resources are limited and to improve people's welfare they should be devoted to those things where they will have the largest positive impact. Rational actors will consider both the likelihood of occurrence and the wellbeing effect of various life events when choosing where to allocate resources. The findings of our research suggest that, at least currently, it is not weather-related house damage but other aspects of people's lives which have the largest impact on their wellbeing.

VII.   Conclusion

As the rate of climate change continues to increase, so too will both the number and severity of weather-related natural disasters. As a result, there is an increasing amount of attention on the damages associated with weather-related natural disasters. These damages have certainly increased, however they are often difficult to accurately quantify. The traditional economic approach to measuring the cost of a disaster focuses on the flow of GDP due to its wide availability and cross-country consistency. However, GDP has several weaknesses when used to measure the impact of disasters. While it measures the economic activity that occurs due to the rebuild effort, it ignores both the loss of capital stock and the opportunity cost of diverting resources to help with the rebuild. It also ignores many non-monetary impacts such as increased stress, environmental harm, and even loss of life.

An alternative approach to using traditional economic techniques to measure the impact of

disasters is the use of subjective wellbeing. In this paper, we contribute to this emerging strand of literature by estimating the impact of experiencing weather-related house damage on subjective wellbeing in Australia using 10 years' worth of panel data. To increase the robustness of our findings, we use a series of data transformations to empirically examine whether our results are robust to changes in the assumed underlying cardinal scale and find they are. We also examine the wellbeing effect of two additional life events: loss of job and relationship breakup.

In general, we find that weather-related house damage has a wellbeing effect which, on average, is small in size and often statistically insignificant. Our main analysis shows that, irrespective of whether we include all respondents or only those that have been affected by weather related house damage, no coefficient estimate is greater than 11.21% of a within-person standard deviation. We find no major difference in wellbeing effect among males and females, or homeowners and non-homeowners. Similarly, the wealthy are unaffected by weather-related house damage. We do find that the poor suffer a decrease in subjective wellbeing which is large in size and statistically significant. When life satisfaction is used as the measure of subjective wellbeing, we find evidence that this decline is long lasting and the poor experience no return to pre-disaster levels of life satisfaction within 3 years after the disaster occurred.

In contrast to the small effect of weather-related house damage, we find that both separation and job loss are associated with a far more significant decline in subjective wellbeing. This decline is large in size and statistical significance and is robust to the use of alternative measures of subjective wellbeing. Our main analysis shows the impact on subjective wellbeing following separation is as large as 48.24% of a within-person standard deviation for separation and 28.25% of a within-person standard deviation for job loss.

There are several reasons which may explain why we find weather-related house damage does not have a significant impact on wellbeing. Firstly, it may be that weather-related house damage truly has no effect on wellbeing and therefore a null result is certain. However, there are other reasons which may explain why we find a null result. Firstly, selection into treatment may occur, so that the people who experience weather-related house damage are also those who are least affected by it. The null result may also be caused by low average damage severity, meaning most people who experienced weather-related house damage experienced

only minor damage. Social comparisons may also explain the null result as an affected person may compare themselves to other affected people, rather than people who did not experience weather-related house damage. Finally, direct financial aid through both high levels of insurance coverage and generous government financial assistance may also explain the null result. Of these possible explanations, selection into treatment, social comparisons, and a low average disaster severity are also consistent with the poor being the most negatively impacted group. As climate change causes disasters to become larger and more widespread, the effects on wellbeing may change with a reasonable assumption being that there will be more of an impact on wellbeing.

Finally, people and governments have limited resources and these resources should be used where they will have the maximum benefit. While people and governments should care about damage done by weather-related natural disasters, they should also care about other life events such as separation and job loss. Our research suggests it is these life events, rather than weather-related house damage, which currently have the largest impact on people's wellbeing.

VIII.   References

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion* (Issue March).

Asadullah, M. N., & Chaudhury, N. (2012). Subjective well-being and relative poverty in rural Bangladesh. *Journal of Economic Psychology*, *33*(5), 940–950. https://doi.org /10.1016/ j.joep.2012.05.003

Bartolini, S., & Sarracino, F. (2014). Happy for how long? How social capital and economic growth relate to happiness over time. *Ecological Economics*, *108*, 242–256. https://doi.org/ 10.1016/j.ecolecon.2014.10.004

Baryshnikova, N. V, & Pham, N. T. A. (2018). *Heterogeneity in the Relationship between Natural Disasters and Mental Health : A Quantile Approach* (No. 2018–13).

Benson, C., & Clay, E. (2004). Understanding the Economic and Financial Impacts of Natural Disasters. In *World Bank Disaster Risk Management Series* (Issue 4). The World Bank. https://doi.org/ 10.1596/0-8213-5685-2

Besstremyannaya, G., & Golovan, S. (2019). Reconsideration of a simple approach to quantile regression for panel data. *The Econometrics Journal*, *22*(3), 292–308. https://doi.org/ 10.1093/ectj/utz012

Bloem, J. R. (2018). *How Much Does the Cardinal Treatment of Ordinal Variables Matter ? An Empirical Investigation*.

Bond, T. N., & Lang, K. (2014). *Using happiness scales to inform policy : Strong words of caution*. Vox. https://voxeu.org/article/using-happiness-scales-inform-policy-strong-words-caution

Bond, T. N., & Lang, K. (2019). The Sad Truth about Happiness Scales. *Journal of Political Economy*, *127*(4), 1629–1640. https://doi.org/10.1086/701679

Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, *13*(2), 167–188. https://doi.org/10.1093/reep/rez004

Brickman, P., & Campbell, D. T. (1971). Hedonic Relativism and Planning the Good Society. In

M. H. Appley (Ed.), *Adaption-Level Theory: A Symposium* (pp. 287–302). New York Academic Press.

Callaway, B., & Li, T. (2019). Quantile treatment effects in difference in differences models with panel data. *Quantitative Economics*, *10*(4), 1579–1618. https://doi.org/10.3982/QE935

Calvo, R., Arcaya, M., Baum, C. F., Lowe, S. R., & Waters, M. C. (2015). Happily Ever After? Pre-and-Post Disaster Determinants of Happiness Among Survivors of Hurricane Katrina. *Journal of Happiness Studies*, *16*(2), 427–442. https://doi.org/10.1007/s10902-014-9516-5

Canay, I. A. (2011). A simple approach to quantile regression for panel data. *The Econometrics Journal*, *14*(3), 368–386. https://doi.org/10.1111/j.1368-423X.2011.00349.x

Carroll, N., Frijters, P., & Shields, M. A. (2009). Quantifying the Costs of Drought: New Evidence from Life Satisfaction Data. *Journal of Population Economics*, *22*(2), 445–461. https://www.jstor.org /stable/40344739?seq=1

Chen, L.-Y., Oparina, E., Powdthavee, N., & Srisuma, S. (2019). Have Econometric Analyses of Happiness Data Been Futile? A Simple Truth About Happiness Scales. *Warwick Business School PrePrint*, 1–23. https://www.researchgate.net/publication/331246440

Clark, A. E., Diener, E., Georgellis, Y., & Lucas, R. E. (2020). Lags and Leads in Life Satisfaction : A Test of the Baseline Hypothesis Published by : Oxford University Press on behalf of the Royal Economic Society Stable URL : https://www.jstor.org/stable/20108833 LAGS AND LEADS IN LIFE SATISFACTION : A TEST OF THE B. *The Economic Journal*, *118*(529). https://www.jstor.org/stable /20108833

Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles. *Journal of Economic Literature*, *46*(1), 95–144. https://doi.org/10.1257/jel.46.1.95

Clark, A. E., & Oswald, A. J. (2002). A simple statistical method for measuring how life events affect happiness. *International Journal of Epidemiology*, *31*, 1139–1144. https://doi.org/ 10.1093/ ije/31.6.1139

Columbia Public Health. (n.d.). *Difference-in-Difference Estimation*. Retrieved October 22, 2020, from https://www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation#:~:text=The parallel trend assumption is,group is constant over time

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences*, *116*(43), 21450–21455. https://doi.org/10.1073/pnas.1907826116

Deloitte. (2016). *The economic cost of the social impact of natural disasters*. https://doi.org/978-982-04-0455-7

Department of Social Services; Melbourne Instituse of Applies Economic and Social Research. (n.d.). *Household, Income and Labour Dynamics in Australia (HILDA), Wave 18 General Release Marked Up Questionnaires*. ADA Dataverse.

Department of Social Services; Melbourne Instituse of Applies Economic and Social Research. (2019). *The Household, Income and Labour Dynamics in Australia (HILDA) Survey, GENERAL RELEASE 18 (Waves 1-18)*. ADA Dataverse. https://doi.org/doi/10.26193/IYBXHM

Di Tella, R., & MacCulloch, R. (2006). Some Uses of Happiness Data in Economics. *The Journal of Economic Perspectives*, *20*(1), 25–46. https://doi.org/10.2307/30033632

Di Tella, R., & MacCulloch, R. (2008). Gross national happiness as an answer to the Easterlin Paradox? *Journal of Development Economics*, *86*(1), 22–42. https://doi.org/10.1016/j.jdeveco. 2007.06.008

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, *29*(1), 94–122. https://doi.org/10.1016/ j.joep.2007 .09.001

Döpke, J., & Maschke, P. (2016). Alternatives to GDP - Measuring the impact of natural disasters using panel data. *Journal of Economic and Social Measurement*, *41*(3), 265–287. https://doi.org /10.3233/JEM-160429

Easterlin, R. A. (1974). Does Economic Growth Improve the Human Lot? Some Empirical Evidence. In *Nations and Households in Economic Growth* (pp. 89–125). Elsevier. https://doi.org/ 10.1016/B978-0-12-205050-3.50008-7

Easterlin, R. A. (2003). *Building a Better Theory of Well-Being* (No. 742; IZA Discussion Paper, Vol. 172).

Ferrer-i-Carbonell, A. (2013). Happiness economics. *SERIEs*, *4*(1), 35–60. https://doi.org/ 10.1007 /s13209-012-0086-7

Ferrer-i-Carbonell, A., & Frijters, P. (2004). How Important Is Methodology for the Estimates of the Determinants of Happiness? *The Economic Journal*, *114*(497), 641–659. https://www.jstor.org/ stable/3590299?seq=1#metadata_info_tab_contents

Frey, B. S., & Stutzer, A. (2002). What can economists learn from happiness research? *Journal of Economic Literature*, *40*(2), 402–435. https://doi.org/10.1257/jel.40.2.402

Friedman, J., More, R., & Reggio, I. (2013). *The often (unspoken) assumptions behind the difference-in-difference estimator in practise*. World Bank Blogs. https://blogs. worldbank.org/ impactevaluations/often-unspoken-assumptions-behind-difference-difference-estimator-practice

Goldberg, L. R. (1993). 'The structure of phenotypic personality traits": Author's reactions to the six comments. *American Psychologist*, *48*(12), 1303–1304. https://doi.org/10.1037 /0003-066x.48.12.1303

Hallegatte, S. (2015). The Indirect Cost of Natural Disasters and an Economic Definition of Macroeconomic Resilience. In *Policy Research Working Papers* (7357, Issue July). http://documents.worldbank.org/curated/en/186631467998501319/The-indirect-cost-of-natural-disasters-and-an-economic-definition-of-macroeconomic-resilience

Hallegatte, S., & Przyluski, V. (2010). The Economics of Natural Disasters: Concepts and Methods. In *Policy Research Working Papers* (Vol. 5507). https://openknowledge. worldbank.org /handle/10986/3991

Hayo, B. (2007). Happiness in transition: An empirical study on Eastern Europe. *Economic Systems*, *31*(2), 204–221. https://doi.org/10.1016/j.ecosys.2006.08.003

Hentschel, S., Eid, M., & Kutscher, T. (2017). The Influence of Major Life Events and Personality Traits on the Stability of Affective Well-Being. *Journal of Happiness Studies*, *18*(3), 719–741. https://doi.org/10.1007/s10902-016-9744-y

Hochrainer, S. (2009). *Assessing the Macroeconomic Impact of Natural Disasters: Are There Any?* (No. 4968; Policy Research Working Paper, Issue June).

Johar, Meliyanni, Peter Siminski, David Johnston, Michael Shield and Olena Stavrunova (2020), The Economic Impacts of Direct Natural Disaster Exposure, IZA DP No. 13616

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, *91*(1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, *46*(1), 33–50. http://links.jstor.org/sici?sici=0012-9682%28197801%2946%3A1%3C33%3ARQ%3E2.0.CO%3B2-J

Koenker, R., Hallock, K. F., Koenker, R., & Hallock, K. F. (2001). Quantile Regression. *The Journal of Economic Perspectives*, *15*(4), 143–156. https://www-jstor-org.ezproxy. canterbury.ac.nz/ stable/2696522

Kousky, C. (2014). Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics*, *46*, 576–592. https://doi.org/10.1016/j.eneco.2013.09.029

Lechner, M. (2010). The estimation of causal effects by difference-in-difference methods. *Foundations and Trends in Econometrics*, *4*(3), 165–224. https://doi.org/10.1561 /0800000014

Lohmann, P., Pondorfer, A., & Rehdanz, K. (2019). Natural Hazards and Well-Being in a Small-Scale Island Society. *Ecological Economics*, *159*(January), 344–353. https://doi.org/10.1016/ j.ecolecon.2018.12.023

Luechinger, S., & Raschky, P. A. (2009). Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics*, *93*(3–4), 620–633. https://doi.org/10.1016/ j.jpubeco.2008.10.003

Luhmann, B. M., & Intelisano, S. (2018). Hedonic Adaptation and the Set Point for Subjective Abstract : Early Historical and Philosophical Accounts. In *Handbook of well-being* (pp. 1–

26). DEF Publishers. https://doi.org/nobascholar.com

Oswald, A. J., & Powdthavee, N. (2008). Does happiness adapt? A longitudinal study of disability with implications for economists and judges. *Journal of Public Economics*, *92*(5–6), 1061–1077. https://doi.org/10.1016/j.jpubeco.2008.01.002

Paul, S., & Guilbert, D. (2013). Income–happiness paradox in Australia: Testing the theories of adaptation and social comparison. *Economic Modelling*, *30*(1), 900–910. https://doi.org/10.1016/j.econmod.2012.08.034

Portillo-Castro, H. (2019). *Emergency management and disaster resilience: a quick guide* (Research Paper Series). https://parlinfo.aph.gov.au/parlInfo/download/library /prspub /6798566/ upload_binary/6798566.pdf

Proctor, C., Tweed, R., & Morris, D. (2015). The Naturally Emerging Structure of Well-Being Among Young Adults: "Big Two" or Other Framework? *Journal of Happiness Studies*, *16*(1), 257–275. https://doi.org/10.1007/s10902-014-9507-6

Rehdanz, K., & Maddison, D. (2005). Climate and happiness. *Ecological Economics*, *52*(1), 111–125. https://doi.org/10.1016/j.ecolecon.2004.06.015

Ryan, R. M., & Deci, E. L. (2001). On Happiness and Human Potentials: A Review of Research on Hedonic and Eudaimonic Well-Being. *Annual Review of Psychology*, *52*(1), 141–166. https://doi.org/10.1146/annurev.psych.52.1.141

Schröder, C., & Yitzhaki, S. (2017). Revisiting the evidence for cardinal treatment of ordinal variables. *European Economic Review*, *92*, 337–358. https://doi.org/10.1016/ j.euroecorev.2016.12.011

Sekulova, F., & van den Bergh, J. C. J. M. (2016). Floods and happiness: Empirical evidence from Bulgaria. *Ecological Economics*, *126*, 51–57. https://doi.org/10.1016/ j.ecolecon. 2016.02.014

Shabnam, N. (2014). Natural Disasters and Economic Growth: A Review. *International Journal of Disaster Risk Science*, *5*(2), 157–163. https://doi.org/10.1007/s13753-014-0022-5

Sheng, Y., & Xu, X. (2019). The productivity impact of climate change: Evidence from Australia's Millennium drought. *Economic Modelling*, *76*(August 2018), 182–191.

https://doi.org/10.1016/ j.econmod.2018.07.031

Skidmore, M., & Toya, H. (2002). Do Natural Disasters Promote Longrun Growth? *Economic Inquiry*, *40*(4), 664–687. https://doi.org/10.1093/ei/40.4.664

Stevenson, B., & Wolfers, J. (2008). Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox. In *Brookings Papers on Economic Activity* (Vol. 1). https://doi.org/ 10.3386/w14282

Stutzer, A. (2004). The role of income aspirations in individual happiness. *Journal of Economic Behavior & Organization*, *54*(1), 89–109. https://doi.org/10.1016/j.jebo.2003.04.003

Tomyn, A. J., Fuller-Tyszkiewicz, M. D., Cummins, R. A., & Norrish, J. M. (2017). The Validity of Subjective Wellbeing Measurement for Children: Evidence Using the Personal Wellbeing Index—School Children. *Journal of Happiness Studies*, *18*(6), 1859–1875. https://doi.org/10.1007/ s10902-016-9804-3

United Nations Office for Disaster Risk Reduction. (2018). Economic Losses, Poverty & Disasters. In *Centre for Research on the Epidemiology of Disasers United Nations Office for Disaster Risk Reduction*. https://www.undrr.org/publication/economic-losses-poverty-disasters-1998-2017

Waterman, A. S. (1993). Two conceptions of happiness: Contrasts of personal expressiveness (eudaimonia) and hedonic enjoyment. *Journal of Personality and Social Psychology*, *64*(4), 678–691. https://doi.org/10.1037/0022-3514.64.4.678

Watson, N., & Wooden, M. (2012). The HILDA Survey: a case study in the design and development of a successful Household Panel Survey. *Longitudinal and Life Course Studies*, *3*(3), 369–381. https://doi.org/10.14301/llcs.v3i3.208

World Meteorological Organization. (2014). *Atlas of Mortality and Economic Losses From Weather, Climate and Water Extremes (1970-2012)* (Issue 1123). World Meteorological Organization. http://www.wmo.int/pages/prog/drr/transfer/2014.06.12-WMO1123_ Atlas_120614.pdf

IX.