I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14220

Resilience to Disaster: Evidence from Daily Wellbeing Data

Paul Frijters
David W. Johnston
Rachel J Knott
Benno Torgler

MARCH 2021

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14220

Resilience to Disaster: Evidence from Daily Wellbeing Data

Paul Frijters
London School of Economics and IZA

David W. Johnston
Monash University

Rachel J Knott
Monash University

Benno Torgler
Queensland University of Technology

MARCH 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Resilience to Disaster: Evidence from Daily Wellbeing Data*

As the severity and frequency of natural disasters become more pronounced with climate change and the increased habitation of at-risk areas, it is important to understand people's resilience to them. We quantify resilience by estimating how natural disasters in the US impacted individual wellbeing in a sample of 2.2 million observations, and whether the effect sizes differed by individual- and county-level factors. The event-study design contrasts changes in wellbeing in counties affected by disasters with that of residents in unaffected counties of the same state. We find that people's hedonic wellbeing is reduced by approximately 6% of a standard deviation in the first two weeks following the event, with the effect diminishing rapidly thereafter. The negative effects are driven by White, older, and economically advantaged sub-populations, who exhibit less resilience. We find no evidence that existing indices of community resilience moderate impacts. Our conclusion is that people in the US are, at present, highly resilient to natural disasters.

JEL Classification: I31, I38

Keywords: wellbeing, resilience, natural disasters, institutions, adaptation

Corresponding author:
Rachel Knott
Centre for Health Economics
Monash University
Caulfield East VIC 3145
Australia

E-mail: rachel.knott@monash.edu

* This research was supported by the Australian Research Council (ARC Discovery Project grant DP170100177).

1. Introduction

In the past few decades, high-hazard areas in the US have become more populated than ever (Cutter and Finch, 2008). For instance, more of America's economic activity is now clustered along its coasts, increasing the risk of exposure to storm and tidal events (Boustan et al., 2020). At the same time, western states − made more socioeconomically vulnerable by warming and frequent droughts, combined with residential expansion − are experiencing an alarming increase in the number and size of wildfires (Schoennagel et al., 2017, Calkin et al., 2014). This has increased the interest in disaster resilience, with the initial focus on improving infrastructure and planning (Eakin et al., 2017).

The social and psychological effects of natural disasters are less well studied than the economic and physical effects (Raphael and Ma, 2011). Yet, natural disasters negatively affect individual mental and physical wellbeing through exposure to physical destruction, loss of resources, environmental changes, personal injury, and disease (Berry et al., 2010). Exposure to such stressors produces indirect costs in the form of poor mental health, anxiety disorders, and diminished quality of life (Kousky, 2014). In addition to general mental health difficulties associated with short-term extreme weather exposure (Obradovich et al., 2018, Mullins and White, 2019), acute weather disasters like floods, forest fires, heat waves, and hurricanes may elicit extreme anxiety reactions like post-traumatic disorder, depression, and even severe psychopathologies (Berry et al., 2010, Salcioglu et al., 2007). In the aftermath of Hurricane Katrina, for example, it is estimated that over half a million individuals required mental health assistance for anxiety, depression, and anger issues (Paul, 2011).

In this study we assess the impact of 'costly' disaster events on wellbeing. Specifically, we merge Federal Emergency Management Agency (FEMA) data on disasters at the county level with individual-level data from the 2008−2015 Gallup Polls, which randomly samples around 1,000 adults across the US each day, providing an estimation sample of over 2.2 million observations.

To optimally target public recovery projects, it is important to understand how quickly individuals bounce back from disasters, and whether some individuals or areas are more affected than others. It is not clear what we should expect: in the wake of Katrina, those with fewer economic resources experienced disproportionately more hardship (Masozera et al., 2007), yet those employed in the construction industry, who are also at the lower end of the economic scale, often benefited from disasters as they were called in to repair the damage (Groen et al., 2020).

Using an event-study design that compares counties directly affected by a disaster with non-affected counties in the same state, we find disasters have a negative impact on wellbeing only in the short-run, with impacts diminishing quickly after the first two weeks following a disaster. Surprisingly, we find the effects to be driven by more economically advantaged individuals; perhaps because they have more to lose or are more risk-averse. Our estimated effects are independent of disaster severity, disaster type, dedicated disaster institutions, and socio-economic measures of community resilience.

These findings contribute to a literature on the wellbeing effects of disastrous events, including the 2011 Great East Japan Earthquake (Rehdanz et al., 2015), 1986 Chernobyl nuclear accident (Danzer and Danzer, 2016), 2001 September 11 terrorist attacks (Metcalfe et al. (2011), 2013 Boston Marathon bombing (Clark et al., 2020), and COVID-19 and associated lockdowns during 2020 (Brodeur et al., 2021). More generally, they contribute to a growing economics literature on the impacts of natural disasters on individual outcomes, such as health (Deyugina et al., 2020), risk preferences (Hanaoka et al., 2018), employment and income (Deyugina et al., 2018), household finances (Gallagher and Hartley, 2017), and religiosity (Bentzen, 2019). Our sample is far larger than most studies in these literatures, which enables our exploration of how effects vary over time, across disaster types, and by individual- and area-level characteristics. The data also enable the exploration of two important but different measures of individual wellbeing: hedonic experiences, which are emotional responses experienced the day before the interview; and life evaluation, which is a reflective evaluation of the respondent's life as a whole.

The magnitude of the found effects puts these FEMA disasters at the lower end of the scale in terms of negative shocks individuals regularly experience on their experiential wellbeing. The magnitude of the effect for a whole month is similar to the effect Clark et al. (2020) found for the Boston Marathon bombing, though they found that effect for the whole country. Like that terrorist event, natural disasters have more effect on experiential (hedonic) measures of wellbeing than evaluative measures. The time effect is also similar in that the effect of the Boston Marathon Bombing lasted one week rather that two weeks for natural disasters.

2. Data

Gallup's US Daily Poll is a unique phone survey which randomly samples around 1,000 adults (aged 18+) across the US every day of the year (excluding major holidays). Originally designed to collect information on public attitudes toward political, social, and economic issues, the survey has also collected data on key factors related to individual wellbeing since 2008. We use data collected between January 2008 and December 2015 for respondents in all contiguous mainland states[1].

Our two outcome measures of interest are experiential/hedonic wellbeing and evaluative wellbeing. The evaluative wellbeing measure is based on the following prompt: "please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?". The experiential/hedonic wellbeing index is the sum of responses to the survey question, did you smile or laugh a lot yesterday? (Y=1/N=0), and the five questions: did you experience the following feelings during a lot of the day yesterday? enjoyment (Y=1/N=0), worry (Y=0/N=1), sadness (Y=0/N=1), stress (Y=0/N=1), and happiness (Y=1/N=0). We rescale the index to have a range of 0 to 10.

The Gallup data are matched to FEMA county-level information on all federally declared US disasters (Federal Emergency Management Agency Disaster Declarations Summary). We focus on all climate and environmental disasters – storms, floods, hurricanes, snow, ice storms, tornados, fires, earthquakes, tsunamis – that received a presidential Major Disaster Declaration enabling affected counties to access a variety of federal assistance programs including public assistance funds and assistance to eligible individuals and households.[2]

In addition to the date each state was first impacted, type of disaster, and counties affected, we incorporate data from FEMA's Public Assistance Funded Projects Summaries dataset. This dataset includes funds allocated to affected counties for the purpose of public emergency work, and replacement or repair of disaster-damaged public assets and facilities. Based on fund

[1] From 2008 to 2012, all survey interviews were conducted using the same survey (~1000 interviews per day). From 2013 onwards the sample was split into two tracks, such that half of daily respondents (~500 per day) complete the Wellbeing survey, while the other half complete the Politics and Economy survey. From this time, our outcome measures of interest were included in the Wellbeing survey only.

[2] We are unable to identify individuals residing on Native American Reservations in the Gallup Poll data, and so we omit FEMA disasters occurring in these locations. However, affected neighbouring counties will be captured.

amounts for projects that received public assistance funds, we identify counties affected by the most severe disaster events during our study period. Our baseline definition of ‘most severe’ is the top 25% of most costly disasters in terms of project costs per affected person; that is, total funds for public assistance projects at the state level (in 2015 dollars) divided by the number of residents in affected counties. Sensitivity of results to this definition are provided.

3. Empirical Approach

To identify the impact of natural disasters on hedonic and evaluative wellbeing, we employ an event-study methodology that compares changes over time in counties directly affected by a disaster with changes over time in other counties from the same state that were not directly affected by the event. We define treatment counties as those that received a presidential Major Disaster Declaration as a result of a particular disaster, and control counties as those that were not subject to a Major Disaster Declaration. As mentioned above, we focus only on disasters that were accorded the highest amounts (top 25%) of public assistance project costs per capita. These events are herein referred to as ‘costly disasters’.

The map in Fig. 1 illustrates this identification approach, and costly disaster definition, using the example of Hurricane Sandy. The effects of this disaster were identified by comparing wellbeing changes over time in treated New York counties with control New York counties. Since all counties in New Jersey were treated, wellbeing changes in this state were not used to identify effects of Hurricane Sandy. Counties in Pennsylvania are not used to identify effects of Hurricane Sandy because the level of per capita public assistance was too low for Sandy to be classified as a ‘costly disaster’ in Pennsylvania.

Empirically, our event-study methodology is based on the following specification:

$$y_{ijt} = \sum_m \beta_m D_{jt-m} + \alpha_j + \tau_t + \gamma_{st} + \delta X_{it} + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} is the outcome of interest for individual i living in county j at time t. α_j contains county-level fixed effects which control for both factors that are common across people living in county j, and the underlying risk of a disaster occurring in j. The term τ_t includes month-year fixed effects that account for events and changes over time occurring at the national level, and day of week fixed effects to control for mood variability across the week. γ_{st} contains state-season-year fixed effects to account for state-specific factors that vary over time. X_{it}

includes characteristics that are specific to the individual: gender, marital status, educational attainment, and race. ε_{ijt} is an idiosyncratic error term.

D_{jt-m} is a vector of m treatment dummies equal to 1 if county j experienced a disaster in time period $t - m$, and zero otherwise. Our coefficient of interest is β_m, which quantifies the extent to which wellbeing is impacted by a natural disaster occurring in time window m surrounding the disaster.[3] Under the assumption that natural disasters occur randomly across time within a given location and time of year, our estimates can be interpreted as causal.

We test the robustness of our estimates to several factors that may affect the validity of our approach. First, response patterns may differ across treatment and control counties after a disaster, which could cause sample selection bias. We examine this issue by including response rates at the county level and number of call attempts to the interviewee as separate variables in the main regression. Secondly, it's possible that the wellbeing of people in our control counties may also be impacted following a disaster, in which case our approach would underestimate the true impacts of disasters. To address this issue, we consider the use of alternate control counties from neighboring states that were not exposed to the disaster. The way in which we define 'costly disasters' may also be problematic. For example, a relatively small disaster may be classified as a costly disaster in our sample if it impacts an area with a small population (inflating the measure of cost per person affected). Similarly, major disasters may be overlooked in our sample if they impact an area with a considerably sized population. To examine this possibility, we consider an alternate definition of costly disasters in terms of overall expenditure at the state level (instead of per capita). We also consider a sample of all natural disasters receiving a Major Disaster Declaration regardless of cost – as opposed to exclusively focusing on costly disasters – to again ensure that our results are not an artefact of sample selection. Finally, we explore the sensitivity of our estimates to the addition of zip code fixed effects and the omission of state-season-year fixed effects.

4. Results

4.1. Main Disaster Impact Estimates

[3] We consider both weekly and monthly time windows, ranging from one month before the disaster to three months post.

Table 1 reports our estimated results for the impacts of natural disasters on hedonic and evaluative wellbeing, with robust standard errors clustered at the county level in parenthesis. Panel A presents results in monthly time windows spanning from one month before to three months after a disaster, while Panel B presents results in weekly time windows from one week before to four weeks after a disaster. The results indicate that hedonic wellbeing declines in the first month after a natural disaster with an estimated 0.08 (3% of a standard deviation) reduction in the index (Panel A). This negative effect is driven primarily by wellbeing decreases of approximately 0.15 (6% of a standard deviation) in the first two weeks following the disaster (Panel B). For context, estimated differences in hedonic wellbeing between men and women, Black and White, and married and single people equal 0.19, 0.32 and 0.44 units, respectively (see Appendix Table A1 which presents the complete set of coefficients for demographic and socioeconomic characteristics). Therefore, the negative hedonic wellbeing effects immediately following disasters are of small-to-moderate size. The negative effect on evaluative wellbeing is smaller and is only significantly different from zero in the one to two weeks following the disaster (p = 0.036). For both hedonic and evaluative wellbeing, the effects of the disaster diminish quickly after two weeks. There are also no significant wellbeing effects in the month (Panel A) or week (Panel B) preceding the disaster; a finding that supports the validity of our methodology.[4]

Disasters appear to impact both positive and negative dimensions of hedonic wellbeing (Appendix Table A3). Specifically, positive affect, measured as the experience of laughter, enjoyment and happiness, is negatively impacted in the first month after the disaster (-0.024, p = 0.030); while negative affect, measured as the experience of worry, sadness, and stress, is positively impacted by a similar magnitude (0.025, p = 0.051).

These results are not sensitive to the use of alternative control groups (Appendix Table A4). Estimates are similar to those in Table 1 when we instead use control counties defined as: (1) counties in other states in the same Standard Federal Region (SFR); (2) counties in other states in the same Bureau of Economic Analysis (BEA) region; (3) counties in other states in the same SFR, removing states that experienced the same disaster but whose public-assistance funded project costs were below the top 25% threshold; and (4) counties in other states in the

[4] We re-estimated equation (1) using a sample of all disasters receiving a presidential Major Disaster Declaration, regardless of their cost (Appendix Table A2). Estimated disaster impacts are smaller using this sample. For example, the week one estimated hedonic wellbeing impact is half the size presented in Table 1 (-0.157 versus -0.079). This is not surprising given that smaller disasters are expected to have smaller wellbeing impacts.

same BEA, again removing states experiencing the same disaster with funding below the cost threshold.

The results are also robust to potentially different survey response patterns following disasters. Results in Appendix Table A5 show that the number of completed surveys in treatment counties drops only slightly in the weeks following disaster: 2.7% in week one and 1.4% in week two. The results also show that adding covariates to the wellbeing regressions that represent county-level response frequency and individual-level number of call attempts does not meaningfully change our disaster impact estimates.

Finally, we tested the sensitivity of the estimated disaster impacts to alternative model specifications (Appendix Table A6). Our findings are relatively insensitive to the addition of zip code fixed-effects, and the omission of state-season-year fixed effects. However, defining expensive disasters in terms of overall expenditure received at the state level, as opposed to expenditure per capita, decreases the estimates. This latter finding suggests that disaster severity is better measured by expenditure per capita.

4.2 Estimates by Disaster Type

To incorporate more contextual information, we disaggregate the analysis by type of disaster (Table 2), relying on the four most frequently occurring events: storms, floods, hurricanes, and snow/ice-related disasters (e.g. snow storms). Given the effects already identified occur only in the first two weeks post disaster, all remaining results consider the combined effect for these weeks only. We find that hedonic wellbeing is most negatively affected by floods (-0.295, p = 0.038) and snow or ice events (-0.256, p = 0.194), with the latter imprecisely estimated due to the small number of affected people. Again, estimated effects for evaluative wellbeing are smaller, with the largest decline occurring after storms (-0.082, p = 0.094).

4.3. Estimates by Disaster Destruction Level

Even within our sample of costly disasters, there is variation in disaster destruction. For instance, disasters within our sample include the 2012 Hurricane Sandy with an associated $1221 per capita for public assistance projects in New York, and the 2011 Hurricane Irene with $56 per capita for public assistance projects in North Carolina. To measure whether the effects on wellbeing vary with disaster destruction, we interact the variable indicating a disaster in the past two weeks with a continuous variable measuring the public assistance project funds received per capita. For ease of interpretation, the latter 'disaster funds per capita' variable was standardized such that the standard deviation equaled one. The results are presented in Appendix Table A7, and show that individuals living in areas with high disaster funds per capita had only slightly lower wellbeing than individuals living in areas with low disaster funds per capita: interaction term *p*-value for hedonic wellbeing equals 0.751.

Disaster funds per capita can be disaggregated to funds provided for 'permanent works' and for 'emergency protection'.[5] Interaction terms with these two disaggregated variables also have imprecisely estimated coefficients: interaction term *p*-values for hedonic wellbeing equal 0.938 for permanent works and 0.427 for emergency protection works. However, the point estimates suggest that disasters that lead to greater emergency protection funds cause greater reductions in hedonic wellbeing. For example, a two standard deviation increase in emergency protection funds per capita is associated with a 0.146 larger decrease in hedonic wellbeing in the two weeks post-disaster. This is the same size as the estimated hedonic wellbeing effect for average-sized disasters, and so moving from an average sized disaster to a very destructive disaster (2 standard deviations higher emergency protection funds) doubles the negative wellbeing effect.

4.4. Heterogeneity in Estimates by Individual and Area Characteristics

Previous research, like Buddelmeyer and Powdthavee (2016), suggests there can be strong differences across individuals in the effects of the same life events (such as, in that study, illness). We explore whether there are individual and area differences in the magnitude of the wellbeing effects of disasters by re-estimating the regression separately along key demographic and socioeconomic factors, including age, gender, race, income, and education. At the individual level, in Table 3 we divide the observations into two groups, defined as high or low on each trait relative to an appropriate threshold, and estimate our models separately for each subsample (e.g., for income levels above/below the sample median). Our results indicate that the negative hedonic wellbeing effects of disasters are larger for people who are: older (-0.207,

[5] Permanent works includes the repair or restoration of a damaged facility to its pre-disaster design, capacity, and function. Emergency protection includes activities conducted to reduce an immediate threat to life, to assist public health and safety, or to protect property that faces an immediate threat of significant damage (FEMA 2007).

$p = 0.001$), White (-0.183, $p < 0.001$), and more socioeconomically advantaged: higher income (-0.156, $p = 0.017$), more highly educated (-0.199, $p = 0.004$), and white-collar workers (-0.202, $p = 0.022$). Combining these more 'vulnerable' groups and re-estimating, we find that the estimated hedonic wellbeing effect for wealthy, older, White people equals -0.295 ($p = 0.006$), while the effect for all remaining people equals -0.105 ($p = 0.076$).

The individual-level differences by income and race are mirrored by area-level heterogeneity analysis (Appendix Table A8). Estimates suggests that counties with higher incomes and more White residents (relative to other counties in the same state) experience a greater decline in hedonic wellbeing following a disaster; however, the estimated effects are not significantly different from one another for income ($p = 0.538$), and only marginally significant for race ($p = 0.079$). In terms of population density, the effect sizes are similar for the above and below median groups.

Supplementary analysis demonstrates that for all the aforementioned subgroups, the negative disaster effects on hedonic wellbeing are concentrated in the first two weeks post-disaster (Appendix Tables A9). A return to pre-disaster levels of wellbeing after two weeks occurs even for the least resilient groups (high socioeconomic status, older, Whites).

4.5 Heterogeneity in Estimates by Community Resilience Indices

Community resilience enables mobilization of collective effort following a disaster, and therefore is expected to reduce collective action problems; serve as effective informal insurance; and provide access to needed information, tools, and assistance (Aldrich, 2012). We explore whether the effects of resilience vary with socioeconomic and structural indicators using the 2015 county-level Baseline Resilience Indicators for Communities (BRIC). These indices are designed to assess a community's disaster resilience, and are based on economic, social, and community factors; as well as critical, environmental, and built infrastructure (Cutter et al., 2014).[6] Using a similar methodological approach to that outlined in Section 4.3, we interact the variable indicating a disaster in the past two weeks with the continuous BRIC indices, standardized to have a mean of zero and standard deviation of one.

[6] There is a large and growing literature that argues numerical resilience indices are crucial for disaster planning at local, regional, and national levels (Scherzer et al., 2019). However, there are notably few robust validation analyses of the proposed resilience indices.

The results in Table 4 show that the estimated wellbeing effects do not vary with the overall resilience index, nor any of the subcomponent resilience indices (social, economic, infrastructural, community, institutional, environmental). In fact, most of the coefficients on the interaction terms are negative, suggesting that people residing in more resilient counties (higher BRIC index scores) experience larger decreases in wellbeing.

Discussion

We matched daily wellbeing data from a large sample of the US population from 2008-2015 (around 2.2 million observations) to county-level information on all US federally declared major natural disasters. We then assessed the effects of costly disasters, and how the effects vary over time, across disaster types, and by individual- and area-level characteristics. Overall, we find that Americans are highly resilient to disasters big enough to trigger a Federal response.

In the first two weeks following a disaster event, people living in disaster-affected counties experience fewer positive emotions and more negative emotions, with the overall hedonic wellbeing scale lowered by around 6% of a standard deviation. This is a small-to-moderate sized effect, approximately equivalent to the estimated average difference in wellbeing between men and women. But the effect is considerably larger for some population subgroups: the negative hedonic wellbeing effect for wealthy, older, White people is roughly three-times larger in magnitude than the effect for all other people. From week three onwards, hedonic wellbeing is similar to pre-disaster levels; for all sub-populations and for all disaster types.

Americans' evaluative wellbeing is mostly unaffected in all periods and for all sub-populations. To put this result into context: a local flood or storm that is bad enough to be declared a federal disaster has an estimated effect on evaluative wellbeing that is similar to a week of being unemployed ((Clark et al., 2008), three days of bad physical health (Frey and Stutzer, 2010; Shields and Price, 2005), or about a month of relatively bad air quality (Ferreira et al., 2013; Luechinger and Raschky, 2009).

The wellbeing resilience to disasters was independent of the Baseline Resilience Index for Communities, which measures the 'usual' protective socio-economic characteristics (wealth, education) and the presence of disaster-oriented institutions. That index is a strong predictor of deaths and destruction involved in these disasters (Bakkensen et al., 2017), but our results show that the higher this 'resource' type of resilience, the stronger the negative effect of the disasters on wellbeing. This effect is insignificant, but still in line with the fact that more affluent individuals are more negatively affected by disasters. One possible reason for this pattern is that the wealthier are more risk-averse and are thus more prepared for disasters, and yet more mentally affected by them when they occur, something also found for health insurance (i.e., Keane & Stavrunova, 2016).

One possibility for the high level of resilience observed is that people easily cope with disasters that do not require the break-up of social life via largescale displacement of populations: our locality-based data by design measures the wellbeing of those who were not displaced. The evidence on Hurricane Katrina, which forced masses to flee, indeed suggested a much stronger effect on wellbeing (Kimball et al., 2006).

In addition, our results might underestimate the effects of disasters because people who are more strongly impacted by disaster are more likely to refuse survey requests. We find that completed surveys in treatment counties declined in the first week following disaster, but only by 2.7%, relative to control counties. Moreover, including the response rate as a regressor to allow for this selectivity makes no substantive difference to the findings, so any bias is likely to be small.

A second potential reason for underestimation is that the control counties are geographically nearby, and therefore their residents may also have experienced some of the same disaster impacts; if only via the media or because they have family in the affected region (Kimball et al., 2006). However, if we instead use control counties from counties further away (e.g. nearby unaffected states), the results are substantially the same.

A wider historical view on disaster resilience gives another perspective. Kenneth Boulding in *The Meaning of the Twentieth Century* (1964) noted on the ability of modern societies to bounce back:

> In 1945, for instance, many of the cities of Germany and Japan lay in almost total ruin. Today it is hard to tell that they were ever destroyed, for they have been completely rebuilt in a space of less than twenty years. It took Western Europe almost three hundred years to recover from the fall of the Roman Empire, and it took Germany decades to recover from the Thirty Years War (1618-1648). It is perhaps an optimistic feature of the present time that as well as great powers of destruction, we have greatly increased powers of recuperation and recovery (Boulding, 1964 pp. 8-9).

Boustan et al. (2017) further noted how technological innovations and improved organizational capacity have meant that large numbers of people and huge amounts of material can be activated towards a disaster zone within hours of any disaster. Disasters are not what they used to be, at least in developed countries.

Our results then suggest that alongside the huge improvement in the ability to overcome the economic and physical effects of disasters, efficient social institutions have emerged that lead to high mental wellbeing resilience, such as support networks via churches, families, the government, and others.

Our findings thus contribute to the shift of attention from physical to social structures generating resilience, whereby the key finding is that there is already a remarkably high level of wellbeing resilience to disasters in place in the US. The key insight that suggests itself for future research is that the main role of the economic and physical disaster infrastructure relevant to wellbeing resilience is to prevent people from having to flee their communities due to disasters (National Research Council, 2012).

References

ALDRICH, D. P. 2012. *Building resilience: Social capital in post-disaster recovery*, University of Chicago Press.

BAKKENSEN, L. A., FOX-LENT, C., READ, L. K. & LINKOV, I. 2017. Validating resilience and vulnerability indices in the context of natural disasters. *Risk Analysis,* 37**,** 982-1004.

BENTZEN, J.S. 2019. Acts of God? Religiosity and natural disasters across subnational world districts. *Economic Journal*, 129, pp. 2295-2321.

BERRY, H. L., BOWEN, K. & KJELLSTROM, T. 2010. Climate change and mental health: a causal pathways framework. *International Journal of Public Health,* 55**,** 123-132.

BOULDING, K. E. 1964. *The meaning of the twentieth century: The great transition*, George Allen & Unwin.

BOUSTAN, L. P., KAHN, M. E., RHODE, P. W. & YANGUAS, M. L. 2020. The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics,* 118**,** 103257.

BOUSTAN, L. P., YANGUAS, M. L., KAHN, M. & RHODE, P. W. 2017. New data set exploring 90 years of natural disasters in the US. *The Conversation*, June 29.

BRODEUR, A., CLARK, A. E., FLECHE, S., & POWDTHAVEE, N. 2021. COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, 193, 104346.

BUDDELMEYER, H., & POWDTHAVEE, N. 2016. Can having internal locus of control insure against negative shocks? Psychological evidence from panel data. *Journal of Economic Behavior & Organization*, 122, 88-109.

CALKIN, D. E., COHEN, J. D., FINNEY, M. A. & THOMPSON, M. P. 2014. How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proceedings of the National Academy of Sciences,* 111**,** 746-751.

CLARK, A. E., DOYLE, O. & STANCANELLI, E. 2020. The Impact of Terrorism on Individual Well-being: Evidence from the Boston Marathon Bombing. *Economic Journal,* 130**,** 2065-2104.

CLARK, A. E., DIENER, E., GEORGELLIS, Y., & LUCAS, R. E. 2008. Lags and leads in life satisfaction: A test of the baseline hypothesis. *The Economic Journal*, 118(529), F222-F243.

CUTTER, S. L., ASH, K. D. & EMRICH, C. T. 2014. The geographies of community disaster resilience. *Global Environmental Change,* 29**,** 65-77.

CUTTER, S. L. & FINCH, C. 2008. Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences,* 105**,** 2301-2306.

DANZER, A. M., & DANZER, N. 2016. The long-run consequences of Chernobyl: Evidence on subjective well-being, mental health and welfare. *Journal of Public Economics*, 135, 47-60.

DERYUGINA, T., KAWANO, L. AND LEVITT, S. 2018. The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10, pp. 202-33.

DERYUGINA, T., & MOLITOR, D. 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina." *American Economic Review*, 110 (11): 3602-33.

EAKIN, H., BOJÓRQUEZ-TAPIA, L. A., JANSSEN, M. A., GEORGESCU, M., MANUEL-NAVARRETE, D., VIVONI, E. R., ESCALANTE, A. E., BAEZA-CASTRO, A., MAZARI-HIRIART, M. & LERNER, A. M. 2017. Urban resilience efforts must consider social and political forces. *Proceedings of the National Academy of Sciences,* 114**,** 186.189.

FEMA. 2007. FEMA Public Assistance Guide. Federal Emergency Management Agency and U.S. Department of Homeland Security, 322/June 2007.

FERREIRA, S., AKAY, A., BRERETON, F., CUÑADO, J., MARTINSSON, P., MORO, M., & NINGAL, T. F. 2013. Life satisfaction and air quality in Europe. *Ecological Economics*, 88, 1-10.

FREY, B. S., & STUTZER, A. 2010. *Happiness and economics: How the economy and institutions affect human well-being*. Princeton University Press.

GALLAGHER, J. AND HARTLEY, D. 2017. Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, 9, pp. 199-228.

GROEN, J. A., KUTZBACH, M. J., & POLIVKA, A. E. 2020. Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, 38(3), 653-685.

HANAOKA, C., SHIGEOKA, H., & WATANABE, Y. 2018. Do risk preferences change? Evidence from the great east japan earthquake. *American Economic Journal: Applied Economics*, 10(2), 298-330.

KEANE, M., & STAVRUNOVA, O. 2016. Adverse selection, moral hazard and the demand for Medigap insurance. *Journal of Econometrics*, 190(1), 62-78.

KIMBALL, M., LEVY, H., OHTAKE, F. & TSUTSUI, Y. 2006. Unhappiness after hurricane Katrina. National Bureau of Economic Research.

KOUSKY, C. 2014. Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics,* 46**,** 576-592.

LUECHINGER, S. & RASCHKY, P. A. 2009. Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics,* 93**,** 620-633.

MASOZERA, M., BAILEY, M. & KERCHNER, C. 2007. Distribution of impacts of natural disasters across income groups: A case study of New Orleans. *Ecological Economics,* 63**,** 299-306.

METCALFE, R., POWDTHAVEE, N., & DOLAN, P. 2011. Destruction and distress: using a quasi-experiment to show the effects of the September 11 attacks on mental well-being in the United Kingdom. *The Economic Journal*, 121(550), F81-F103.

MULLINS, J. T. & WHITE, C. 2019. Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics,* 68**,** 102240.

NATIONAL RESEARCH COUNCIL 2012. *Disaster resilience: A national imperative*, Washington, DC: The National Academies Press.

OBRADOVICH, N., MIGLIORINI, R., PAULUS, M. P. & RAHWAN, I. 2018. Empirical evidence of mental health risks posed by climate change. *Proceedings of the National Academy of Sciences,* 115**,** 10953-10958.

PAUL, B. K. 2011. *Environmental hazards and disasters: contexts, perspectives and management*, John Wiley & Sons.

RAPHAEL, B. & MA, H. 2011. Mass catastrophe and disaster psychiatry. *Molecular Psychiatry,* 16**,** 247-251.

REHDANZ, K., WELSCH, H., NARITA, D. & OKUBO, T. 2015. Well-being effects of a major natural disaster: The case of Fukushima. *Journal of Economic Behavior & Organization,* 116**,** 500-517.

SALCIOGLU, E., BASOGLU, M. & LIVANOU, M. 2007. Post-traumatic stress disorder and comorbid depression among survivors of the 1999 earthquake in Turkey. *Disasters,* 31**,** 115-129.

SCHOENNAGEL, T., BALCH, J. K., BRENKERT-SMITH, H., DENNISON, P. E., HARVEY, B. J., KRAWCHUK, M. A., MIETKIEWICZ, N., MORGAN, P., MORITZ, M. A. & RASKER, R. 2017. Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences,* 114**,** 4582-4590.

SHIELDS, M. A., & PRICE, S. W. 2005. Exploring the economic and social determinants of psychological well-being and perceived social support in England. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 168(3), 513-537.

Figure 1. Illustration of identification approach

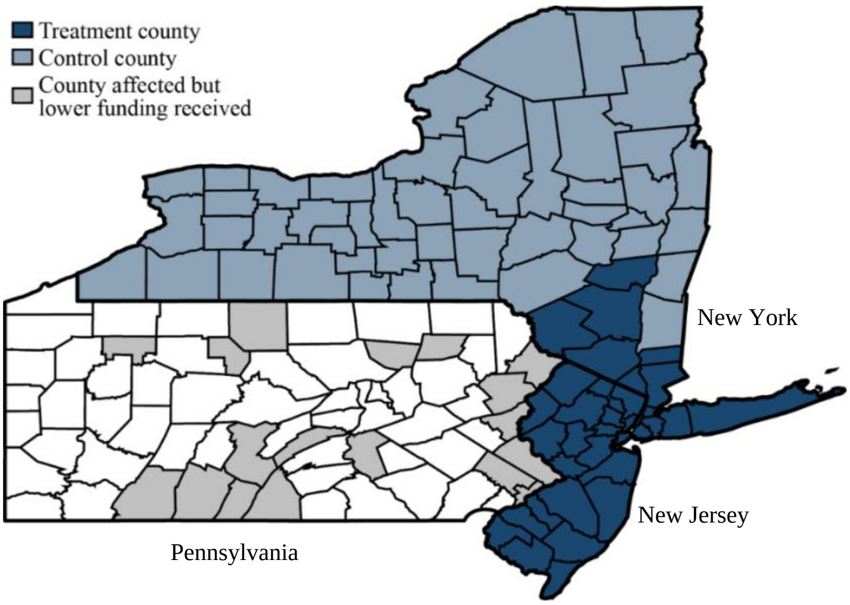

Fig. 1. Treatment and control groups for New York, New Jersey, and Pennsylvania with respect to Hurricane Sandy. Disaster-affected counties (treatment group) experienced a costly disaster that received a presidential Major Disaster Declaration and are colored dark blue; other counties in the same state that did not receive a presidential Major Disaster Declaration for the particular disaster serve as the control group and are colored in light blue. While some counties in Pennsylvania received a Major Disaster Declaration for Hurricane Sandy (grey), the state received a lower level of public funds per person, thus variation here is not used to identify our estimates. See Appendix Figure A1 for all treatment and control counties during the 2008-2015 period.

Table 1. Hedonic and evaluative wellbeing post disaster

	Hedonic Wellbeing		Evaluative Wellbeing	
(A) Monthly to 3 months				
Lead: 0-1 month	0.023	(0.029)	0.021	(0.023)
0-1 month	-0.081**	(0.034)	0.002	(0.025)
1-2 months	-0.045	(0.029)	0.022	(0.023)
2-3 months	0.041	(0.030)	-0.021	(0.022)
(B) Weekly to 4 weeks				
Lead 0-1 week	0.045	(0.053)	0.037	(0.045)
0-1 week	-0.157**	(0.064)	0.024	(0.047)
1-2 weeks	-0.138**	(0.066)	-0.094**	(0.045)
2-3 weeks	-0.054	(0.063)	0.058	(0.047)
3-4 weeks	-0.013	(0.061)	-0.017	(0.043)
Outcome sample mean	7.914		6.993	
Outcome std deviation	2.620		1.967	
Sample size	2,217,717		2,189,185	

*Note*s: Whereas Panel A reports the decline in hedonic and evaluative wellbeing in the first three months after a natural disaster, Panel B considers week-by-week effects during the first month. The treatment is a binary variable equal to 1 if the county experienced a major disaster whose public assistance (PA)-funded project costs per capita were in the top 25% during the time period. All models include county fixed effects (FE), month-year FE (national), state-season-year FE, day of week FE, and the independent variables of age, age squared, gender, marital status, education, and race. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Hedonic and evaluative wellbeing by disaster type: First two weeks post disaster

	Hedonic Wellbeing		Evaluative Wellbeing	
Storms	-0.094	(0.064)	-0.082*	(0.049)
Floods	-0.295**	(0.143)	-0.042	(0.086)
Hurricanes	-0.135*	(0.082)	0.023	(0.049)
Snow or Ice	-0.256	(0.197)	-0.028	(0.124)

Notes: This table disaggregates the main results from Table 1 by the four major (most frequent) disaster types. All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables (age, age squared, gender, marital status, education, and race). Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Individual-level heterogeneity effects: First two weeks post disaster

	Sample size	Hedonic Wellbeing		Evaluative Wellbeing	
Income below median	845,122	-0.092	(0.076)	-0.047	(0.056)
Income above median	945,615	-0.156**	(0.065)	-0.029	(0.045)
Education: no degree	1,269,010	-0.101*	(0.061)	-0.056	(0.044)
Education: college degree	948,707	-0.199***	(0.070)	-0.008	(0.042)
Occupation is blue collar	317,066	-0.088	(0.116)	-0.133	(0.087)
Occupation is white collar	660,439	-0.202**	(0.088)	-0.034	(0.062)
Race is nonwhite	459,406	0.013	(0.099)	-0.054	(0.074)
Race is white	1,758,311	-0.183***	(0.050)	-0.036	(0.034)
Age < 40 years	496,578	-0.001	(0.083)	-0.033	(0.070)
Age 40 to 59 years	791,050	-0.158*	(0.089)	-0.079	(0.055)
Age ≥ 60 years	930,089	-0.207***	(0.064)	0.004	(0.053)
Gender is female	1,119,108	-0.167***	(0.061)	-0.053	(0.044)
Gender is male	1,098,609	-0.123*	(0.065)	-0.018	(0.043)

Notes. All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables of age, age squared, gender, marital status, education, and race. Income is binary coded as high versus low in relation to the (approximate) sample median, while education is divided into no college degree versus college degree. Occupation is divided into white versus blue collar workers, but because these data are only available for ~45% of the observations, the sample size is smaller. Reported sample sizes are for mental wellbeing regressions; sample sizes for life satisfaction regressions are similar. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Baseline community resilience indicators: BRIC scores

		Hedonic Wellbeing		Evaluative Wellbeing	
(A) Overall resilience score					
	Disaster x overall resilience score	-0.040	(0.038)	-0.018	(0.026)
	Disaster in past 2 weeks	-0.138***	(0.045)	-0.035	(0.031)
(B) Subcomponent resilience scores					
i.	Disaster x social resilience score	-0.044	(0.033)	-0.031	(0.024)
	Disaster in past 2 weeks	-0.144***	(0.046)	-0.038	(0.030)
ii.	Disaster x economic resilience score	-0.049	(0.034)	-0.018	(0.024)
	Disaster in past 2 weeks	-0.151***	(0.047)	-0.040	(0.030)
iii.	Disaster x infrastructural resilience score	-0.024	(0.036)	0.047*	(0.025)
	Disaster in past 2 weeks	-0.143***	(0.047)	-0.042	(0.030)
iv.	Disaster x community resilience score	0.013	(0.042)	-0.041	(0.030)
	Disaster in past 2 weeks	-0.148***	(0.047)	-0.028	(0.030)
v.	Disaster x institutional resilience score	0.016	(0.042)	0.000	(0.025)
	Disaster in past 2 weeks	-0.151***	(0.048)	-0.038	(0.032)
vi.	Disaster x environmental resilience score	-0.046	(0.040)	-0.041*	(0.024)
	Disaster in past 2 weeks	-0.147***	(0.046)	-0.040	(0.030)

Notes: Using the 2015 Baseline Resilience Indicators for Communities scores, we estimate seven separate models: interactions with the standardized summary score (Panel A) and separate models with interactions for each of the standardized subcomponents (Panel B). All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables (age, age squared, gender, marital status, education, and race). Robust standard errors are clustered at county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Online Appendix

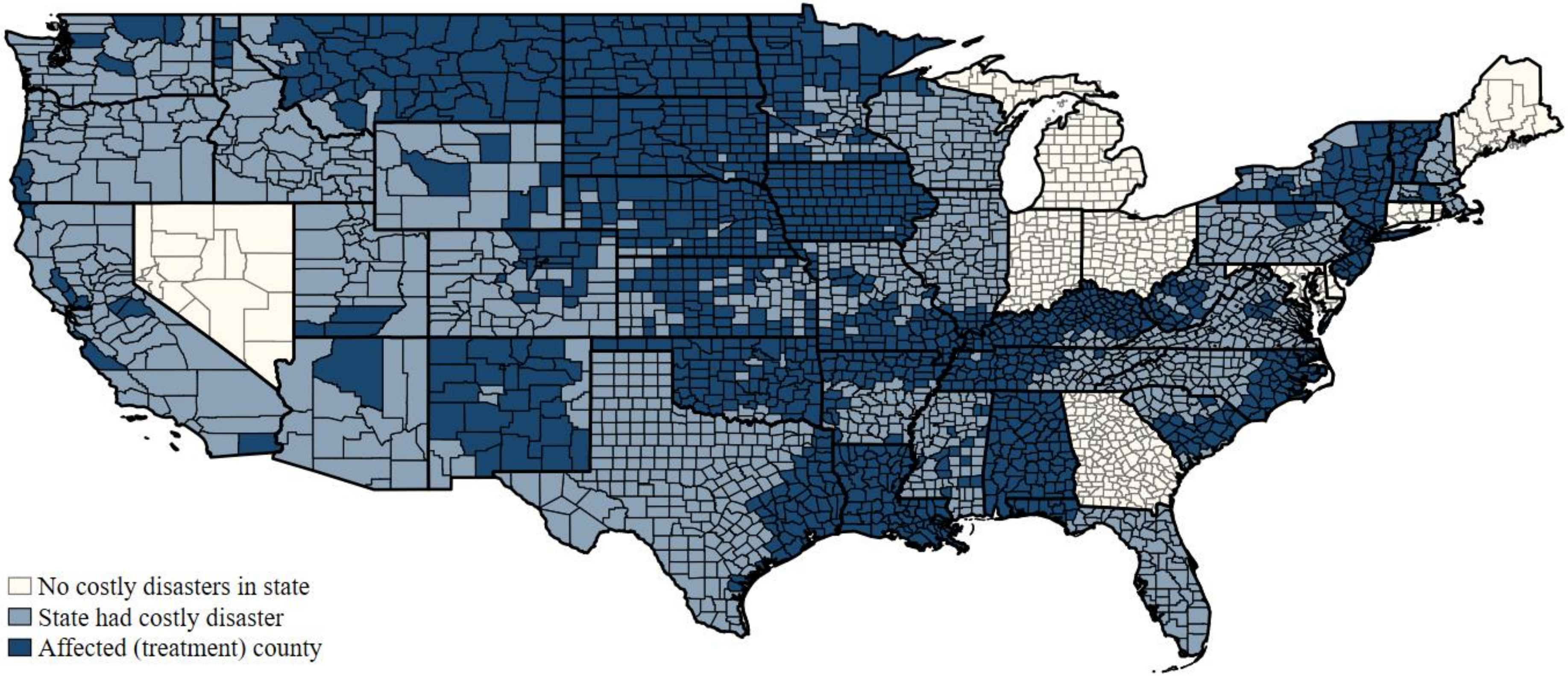

Fig. A1. Counties and states that experienced a major costly natural disaster. The dark blue counties experienced (at least one) major costly natural disaster during the 2008-2015 study period. Counties in states that experienced a large disaster but did not receive a major disaster declaration for a costly natural disaster during the 2008-2015 period are colored in the lighter blue. Black outlines mark state borders.

Appendix Tables

Table A1. Coefficients on demographic and socioeconomic characteristics from main specification

	Hedonic Wellbeing	Evaluative Wellbeing
Disaster during past 2 weeks	-0.145***	-0.038
	(0.047)	(0.031)
Age	-0.075***	-0.059***
	(0.001)	(0.001)
Age squared	0.001***	0.001***
	(0.000)	(0.000)
Female	-0.190***	0.245***
	(0.004)	(0.003)
Married	0.437***	0.484***
	(0.006)	(0.005)
Separated/divorced	-0.346***	-0.225***
	(0.011)	(0.007)
Widowed	-0.070***	0.004
	(0.009)	(0.007)
High school graduate	0.681***	0.283***
	(0.012)	(0.008)
Trade	0.655***	0.242***
	(0.014)	(0.011)
Some college	0.758***	0.387***
	(0.012)	(0.009)
Bachelor's degree	0.935***	0.728***
	(0.014)	(0.010)
Postgraduate degree	0.975***	0.986***
	(0.015)	(0.010)
Black	0.322***	0.105***
	(0.012)	(0.008)
Asian	0.059***	-0.077***
	(0.016)	(0.010)
Hispanic	0.082***	0.162***
	(0.016)	(0.009)
Other race	-0.167***	-0.146***
	(0.015)	(0.012)

Notes: This table reports the coefficients of the respondent-level characteristics of the models in Table 1. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A2. All major disasters (regardless of cost)

	Hedonic wellbeing		Evaluative wellbeing	
(A) Monthly to 3 months				
Lead: 0-1 month	-0.000	(0.012)	0.004	(0.009)
0-1 month	-0.028**	(0.012)	0.010	(0.009)
1-2 months	-0.023*	(0.012)	0.004	(0.009)
2-3 months	0.004	(0.013)	-0.004	(0.009)
(B) Weekly to 4 weeks				
Lead 0-1 week	-0.007	(0.022)	0.001	(0.017)
0-1 week	-0.079***	(0.024)	0.032*	(0.016)
1-2 weeks	-0.034	(0.023)	-0.013	(0.017)
2-3 weeks	-0.009	(0.023)	0.010	(0.017)
3-4 weeks	-0.002	(0.022)	0.014	(0.018)
Outcome sample mean	7.914		6.993	
Outcome std deviation	2.620		1.967	
Sample size	2,217,717		2,189,185	

Notes: The independent variables are the same as in Table 1 but include a dummy equal to 1 if the residents experienced any natural disaster receiving a presidential Major Disaster Declaration (not simply a costly one). The control group here includes people living in other counties of the same state that did not receive a Major Disaster Declaration for the particular disaster. All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables (age, age squared, gender, marital status, education, and race). Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3. Positive and negative affect post disaster

	Positive Affect		Negative Affect	
(A) Monthly to 3 months				
Lead: 0-1 month	0.008	(0.009)	-0.004	(0.011)
0-1 month	-0.024**	(0.011)	0.025*	(0.013)
1-2 months	-0.010	(0.009)	0.015	(0.011)
2-3 months	0.010	(0.010)	-0.015	(0.012)
(B) Weekly to 4 weeks				
Lead 0-1 week	0.013	(0.017)	-0.016	(0.021)
0-1 week	-0.042*	(0.022)	0.053**	(0.023)
1-2 weeks	-0.028	(0.021)	0.049*	(0.025)
2-3 weeks	-0.014	(0.020)	0.020	(0.025)
3-4 weeks	-0.023	(0.020)	-0.012	(0.023)
Outcome sample mean	2.568		0.820	
Outcome std deviation	0.852		1.041	
Sample size	2,224,529		2,241,002	

Notes: Panel A reports changes in positive and negative affect in the first three months after a natural disaster, and Panel B considers week-by-week effects during the first month. Positive affect is the sum of the three positive binary response variables used to construct the mental wellbeing index (smile/laugh, enjoyment, happiness); while negative affect is the sum of the three negative variables used for the index (worry, sadness, and stress). The treatment is a binary variable equal to 1 if the county experienced a major disaster whose public assistance (PA)-funded project costs per person were in the top 25% during the time period. All models include county fixed effect (FE), month-year FE (national), state-season-year FE, day of week FE, and the independent variables of age, age squared, gender, marital status, education, and race. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A4. Estimates using alternative control counties

	Hedonic Wellbeing				Evaluative Wellbeing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead 0-1 week	0.050	0.048	0.019	0.016	0.038	0.036	0.036	0.033
	(0.052)	(0.052)	(0.054)	(0.054)	(0.044)	(0.044)	(0.045)	(0.045)
0-1 week	-0.151**	-0.153**	-0.149**	-0.151**	0.031	0.029	0.032	0.030
	(0.062)	(0.062)	(0.062)	(0.062)	(0.046)	(0.046)	(0.047)	(0.047)
1-2 weeks	-0.140**	-0.140**	-0.155**	-0.155**	-0.090**	-0.090**	-0.098**	-0.100**
	(0.065)	(0.065)	(0.065)	(0.065)	(0.043)	(0.043)	(0.043)	(0.043)
2-3 weeks	-0.051	-0.052	-0.071	-0.072	0.058	0.059	0.066	0.065
	(0.061)	(0.061)	(0.062)	(0.062)	(0.045)	(0.045)	(0.046)	(0.046)
3-4 weeks	-0.013	-0.010	-0.023	-0.021	-0.016	-0.011	-0.010	-0.005
	(0.060)	(0.060)	(0.060)	(0.060)	(0.043)	(0.043)	(0.044)	(0.044)
Outcome mean	7.914	7.914	7.916	7.916	6.993	6.993	6.997	6.997
Outcome st dev	2.620	2.620	2.618	2.618	1.967	1.967	1.966	1.966
N	2217717	2217717	2030369	2030369	2189185	2189185	2003978	2003978

*Note*s: Counties in treated states are compared to counties in other states in the same Standard Federal Region (combining regions I and II) in columns (1) and (5), and the same Bureau of Economic Analysis (BEA) region in columns (2) and (6). Similarly, counties in treated states are compared to counties in other states in same Standard Federal Region in columns (3) and (7), and in the same BEA region in columns (4) and (8), however states that experienced the same disaster were removed from these analyses if their public-assistance funded total project costs per capita were below the top 25% threshold. All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables of age, age squared, gender, marital status, education, and race. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A5. Effects of disasters on survey response

	Number call attempts (log)	Response frequencies (log)	Hedonic Wellbeing	Evaluative Wellbeing
Lead 0-1 week	0.011	0.014	0.045	0.036
	(0.012)	(0.011)	(0.053)	(0.045)
0-1 week	-0.019	-0.027**	-0.157**	0.025
	(0.014)	(0.012)	(0.064)	(0.047)
1-2 weeks	-0.040***	-0.014	-0.137**	-0.093**
	(0.012)	(0.012)	(0.066)	(0.045)
2-3 weeks	-0.019	-0.013	-0.053	0.059
	(0.013)	(0.011)	(0.063)	(0.047)
3-4 weeks	-0.028**	0.016	-0.012	-0.016
	(0.011)	(0.011)	(0.061)	(0.043)
Number call attempts (log)	-	-	0.017***	0.041***
			(0.003)	(0.003)
Response frequencies (log)	-	-	-0.009*	-0.006
			(0.005)	(0.004)
Outcome sample mean	0.579	0.444	7.914	6.993
Outcome std deviation	0.551	0.798	2.620	1.967
Sample size	2249774	1293344	2217717	2189185

Notes: This table reports the impacts of natural disasters on the number of call attempts (log) and response frequencies (log); alongside the hedonic and evaluative wellbeing regressions of Table 1 with the inclusion of call attempts and response frequencies. The maximum number of call attempts is capped at seven for this analysis, as the maximum varies across years. Response frequencies are the total number of responses at the county-week-year (including zeros for non-response). The treatment for the first (call attempts), third (hedonic wellbeing), and fourth (evaluative wellbeing) columns is a binary variable equal to 1 if the respondent resides in a county that experienced a major disaster, defined as disaster whose public assistance-funded project costs per capita were in the top 25% during the time period. The treatment for the second column (response frequency) is a binary variable equal to 1 if a county experienced a major disaster during the time period, regardless of whether responses were collected during the period. All models include county FE, month-year FE (national) and state-season-year FE. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A6. Robustness checks

	Hedonic Wellbeing	Evaluative Wellbeing
Model (1)	-0.145***	-0.038
	(0.047)	(0.031)
Model (2)	-0.149***	-0.040
	(0.046)	(0.034)
Model (3)	-0.133***	-0.023
	(0.045)	(0.029)
Model (4)	-0.066***	0.014
	(0.023)	(0.015)

Notes: All coefficients refer to a dummy variable for two weeks post disaster (as in Tables 2-4). We estimate four different models: (1) baseline model; (2) zip code instead of county fixed effects; (3) no state-season-year fixed effects; and (4) examining the most expensive disasters (top 25%) in terms of total costs per state (not per person in affected counties). *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A7. Expenditure amount and type: Standardized funds per affected person

	Hedonic Wellbeing		Evaluative Wellbeing	
(A) All funds				
Disaster in past 2 weeks	-0.143***	(0.047)	-0.043	(0.031)
Disaster x standardized disaster funds / capita	-0.017	(0.053)	0.038	(0.026)
(B) Funds by category				
Disaster in past 2 weeks	-0.146***	(0.047)	-0.044	(0.031)
Disaster x standardized permanent works funds / capita	0.003	(0.039)	0.025	(0.020)
Disaster x standardized emergency protection funds / capita	-0.073	(0.092)	0.011	(0.053)
Outcome sample mean	7.914		6.993	
Outcome std deviation	2.620		1.967	
Sample size	2,217,717		2,189,185	

Notes: This table considers standardized state funds per person in the affected counties (see Appendix Table A8 for standardized total funds), with funding received in the first two weeks and based on the top 25% most costly disasters. The treatment is a continuous interaction term: experienced top 25% disaster over time period*funding received per capita, standardized across 25% most costly disasters. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A8. County-level heterogeneity effects: First two weeks post disaster

	Sample size	Hedonic Wellbeing		Evaluative Wellbeing	
Average income < state average	1,144,028	-0.118*	(0.060)	-0.023	(0.042)
Average income ≥ state average	1,073,689	-0.176**	(0.071)	-0.055	(0.044)
Proportion white < state average	885,985	-0.047	(0.073)	-0.031	(0.049)
Proportion white ≥ state average	1,331,732	-0.212***	(0.059)	-0.050	(0.038)
Pop density < state average	668,572	-0.160**	(0.068)	-0.046	(0.050)
Pop density ≥ state average	1,549,145	-0.126**	(0.063)	-0.033	(0.038)

Notes: All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables (age, age squared, gender, marital status, education, and race). Income refers to the median county income below/above the state median; race designates the county proportion of Whites below/above the state average; and population density is the county population per square mile above/below state density. Reported sample sizes are for mental wellbeing regressions; sample sizes for life satisfaction regressions are similar. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A9. Individual- and county-level heterogeneity effects in Hedonic Wellbeing: First four weeks post disaster

	0-1 week		1-2 weeks		2-3 weeks		3-4 weeks	
PANEL A: Individual-level effects								
Income below median	-0.053	(0.113)	-0.122	(0.103)	-0.099	(0.099)	-0.013	(0.099)
Income above median	-0.198**	(0.092)	-0.115	(0.087)	-0.006	(0.082)	0.049	(0.085)
Education: low	-0.094	(0.087)	-0.110	(0.084)	-0.012	(0.082)	0.034	(0.082)
Education: high	-0.248**	(0.097)	-0.170*	(0.096)	-0.121	(0.090)	-0.078	(0.091)
Occupation is blue collar	-0.070	(0.171)	-0.119	(0.152)	-0.165	(0.179)	-0.091	(0.132)
Occupation is white collar	-0.178	(0.122)	-0.223*	(0.122)	0.016	(0.104)	-0.114	(0.096)
Race is nonwhite	0.013	(0.157)	0.008	(0.128)	-0.107	(0.111)	-0.035	(0.146)
Race is white	-0.194***	(0.070)	-0.182**	(0.072)	-0.052	(0.071)	-0.012	(0.063)
Age < 40 years	-0.076	(0.122)	0.062	(0.118)	-0.015	(0.130)	0.003	(0.125)
Age 40 to 59 years	-0.220*	(0.113)	-0.133	(0.126)	-0.134	(0.110)	-0.165	(0.107)
Age ≥ 60 years	-0.127	(0.091)	-0.271***	(0.093)	-0.022	(0.097)	0.104	(0.081)
Gender is female	-0.206**	(0.082)	-0.138	(0.091)	-0.007	(0.084)	-0.068	(0.090)
Gender is male	-0.117	(0.094)	-0.135	(0.085)	-0.111	(0.093)	0.053	(0.081)
PANEL B: County-level effects								
Income < state median	-0.139*	(0.083)	-0.089	(0.084)	-0.045	(0.086)	0.081	(0.080)
Income > state median	-0.182*	(0.100)	-0.204**	(0.097)	-0.070	(0.093)	-0.122	(0.089)
% white < state median	-0.120	(0.109)	-0.009	(0.094)	-0.144	(0.097)	-0.019	(0.107)
% white > state median	-0.184**	(0.079)	-0.236***	(0.085)	-0.013	(0.082)	-0.021	(0.074)
Pop density < state median	-0.233**	(0.092)	-0.084	(0.095)	-0.030	(0.107)	-0.011	(0.093)
Pop density ≥ state median	-0.090	(0.087)	-0.173**	(0.088)	-0.073	(0.077)	-0.014	(0.080)

Notes. All models include county FE, month-year FE (national), state-season-year FE, day of week FE, and the independent variables of age, age squared, gender, marital status, education, and race. Age is binary coded as older (over 55) versus younger (under 55) and income as high versus low in relation to the (approximate) sample median. Occupation is divided into white versus blue collar workers, but because these data are only available for ~45% of the observations, the sample size is smaller. Robust standard errors are clustered at the county level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.