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More than a feeling: A global economic valuation of subjective wellbeing damages resulting from rising temperatures

Stephan Dietrich and Stafford Nichols

More Than a Feeling: A Global Economic Valuation of Subjective Wellbeing Damages resulting from Rising Temperatures

Stephan Dietrich[†] and Stafford Nichols[*]

Abstract:

Climate impact models are forced to make sweeping assumptions when estimating social and economic welfare damages to countries around the world, because of a lack of data and understanding of local causal mechanisms. In this paper, we estimate the effects of rising temperatures on countries around the world using an experienced utility approach, based on subjective wellbeing survey data collected in 160 countries for 13 years. We take advantage of 40 years of variation in daily land surface temperature data, to find that one exceptionally hot day significantly lowers wellbeing. Furthermore, the effect size varies substantially between and within countries. Identifying this high degree of heterogeneity is important because it illustrates the shortcomings of many current models which are geographically coarse. Moreover, we compare the marginal utility of income and non-income effects and find that income accounts for only a small proportion of the damages caused by extreme temperatures. This demonstrates the adverse effect on non-market goods is dramatically higher than previously assumed, which indicates current models are missing a fundamental source of climate-related damages.

Keywords:

Climate Policy, Subjective Wellbeing, Climate Damages, Social Cost of Carbon, Global Warming

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1. Introduction

Establishing the impact that climate change has on society is critical. For example, U.S. Policymakers have relied on one measure, the Social Cost of Carbon, to allocate roughly $1 trillion (Rode et al. 2021). The Social Cost of Carbon is based on Integrated Assessment Models (IAMs), which provide laudable attempts to connect climate change effects to social and economic welfare damages (Nordhaus 2014; Stern 2006). However, IAMs are based on sparse data points collected from rich western countries and have very little theoretical underpinning for most of their assumptions and chosen parameters (Pindyck 2013; Stern 2022; Revesz et al. 2014). In this paper, we seek to quantify the effects that rising temperatures have on the subjective wellbeing of populations across the globe using a novel approach and 13 years of globally representative data.

We combine two streams of climate research. The first stream is the global climate econometrics literature regarding the monetization or quantification of damages to society caused by climate change. Economists have modeled this complex relationship for decades with increasing sophistication in order to give policymakers tools to conduct cost-benefit analysis around the tradeoffs between economic development and adverse environmental consequences (Drupp and Hänsel, 2021; Nordhaus, 2018).

The second stream of research focuses on evaluating non-market and environmental goods, using an experienced utility approach based on subjective wellbeing (SWB) (Welsch and Kühling 2009; Zapata 2022; Jones 2018). This research uses ex-post SWB to measure intangible factors such as mental health effects (Fernandez, Stoeckl, and Welters 2019; Yoo et al. 2022). It has allowed researchers to estimate the value of non-monetary goods such as water quality, air pollution, and lifestyle. (Newbold and Johnston 2020; Zhang, Zhang, and Chen 2017; Cheng et al. 2021; Krekel and Zerrahn 2017)

We argue that current international models fail to fully incorporate non-market goods in which climate change may affect individuals' lives and therefore inaccurately value climate change damages. Missing price signals of these non-market goods make them particularly difficult to monetize. To address this shortcoming, we apply an experienced utility approach to a global database of subjective wellbeing (SWB) data from 160 countries, conducted across 13 years, which incorporates 40 years of daily land surface temperature. A range of environmental economic papers use SWB measures to value environmental public goods using an experienced utility approach (see for example Luechinger 2009; Luechinger and Raschky 2009; Ren, and Folmer 2020; van Hoorn 2018). The underlying idea of this approach is to compute the marginal rate of substitution between the marginal utility of income and the marginal utility of the environmental good, where utility is approximated by SWB reports.

Consequently, the marginal benefits and costs of a non-market good can be estimated with SWB data.

Unlike previous models that assume a series of specific causal relationships between global warming and wellbeing, our approach simply looks at how wellbeing changes as the people experience higher temperatures. The SWB construct used in this analysis is Life Evaluation, an umbrella indicator that allows respondents to consider and weigh any factor that they deem important in their lives, and does not rely on researchers deciding what factors to include and calibrate (Kahneman and Krueger 2006). This subjective measure provides a broad net with which to capture and value climate change impacts. This is an appropriate approach because the warming of the planet is a complex global natural phenomenon that affects lives in known and unknown ways. However, the broad encompassing nature of this approach also means that it does not allow for a detailed factor analysis of specific causal mechanisms. We partially address this by examining the primary determinant in SWB, wealth (Diego-Rosell, Tortora, and Bird 2018). We split climate change effects on SWB into income and non-income effects, which also allows us estimate a monetary value of these effects.

This paper studies the impacts of rising temperatures because that is the central climate change issue addressed in the key climate policy frameworks, such as the Paris Climate Agreement. We establish an empirical framework that allows us to estimate the effects of "high temperature days" (HTD) on SWB, and examine how the effects differ by region and demographic group. To better understand causal mechanisms, we separate out the effect of HTD on SWB through income and non-income channels. Generally, income is the largest factor in SWB (Diego-Rosell, Tortora, and Bird 2018), so we were surprised to find that HTD effect SWB mostly thought non-income related channels. Our empirical approach focuses on the short-term, so it possibly underestimates income effects that would play out over a longer period of time. Nonetheless, this is important because current climate impact models focus on monetary effects (Warren et al. 2021) and are probably missing many non-monetary effects (Auffhammer 2018).

Understanding the relative size of income and non-income effects, also allows us to take the analysis one step further, and compute the income growth necessary to compensate for the loss of SWB caused by these increasingly frequent HTD. This provides us with a global model to quantify and value the damage caused to SWB by climate change, and sheds light on the strengths and limitations of current econometric models used to value climate change's economic damages.

This paper contributes to our understanding of how global warming affects wellbeing in several ways. First it focuses on 'climate' effects and not 'weather' effects on SWB. Second, it provides global estimates that include many low-income and lower-middle income countries

– some of which have never had data included in climate econometric modeling. Third, it is based on sub-national statistics which help highlight the level of variation within countries, and the heterogeneity of effects. Fourth, it uses a structural equation model to differentiate between income and non-income effects on SWB, providing insight into the size of the two main theoretical causal pathways. Fifth, it uses a valuation framework to monetize these damages and helps us value them economically, which is useful from a policy making perspective.

Section 2 discusses how this approach relates to existing studies on climate change and well-being. Section 3 explains the construction of the dataset, and how it allows us to target sub-national regions in each country. Section 4 provides an overview of our empirical approach where we compare SWB of respondents in the same region and year who were differently exposed to high temperatures. In Section 5 we explore the results and implications of this initial modeling, before examining the income and non-income effects in Section 6. This section also estimates these results moving forward, by extending our model into the future to examine what income growth would be required to compensate for the loss of SWB to HTD. Finally, in Section 7, we discuss our results and their implications for relevant literature and policy frameworks.

2. Background

Researchers in the 1990s began creating integrated assessment models to estimate the relationship between higher concentrations CO_2 changing climate patterns, and resulting physical and economic impacts (Pindyck 2013). A central component of IAMs is the calculation and underlying assumptions of the "damage function", which translates rising global temperatures into impacts on society (Stern 2006).

IAMs are used to calculate critical policy tools such as the Social Cost of Carbon (SCC), the price tag that the United States Government attributes to the emitting one additional ton of CO_2 (Warren et al. 2021). The SCC is used to conduct environmental evaluations and approve or disapprove billions of dollars of projects. Researchers have done a laudable job at trying to update and append additional modules to IAMs over the years to include other aspects of climate damages. However, there remains serious fundamental disagreements with how IAMs should be calculated (Sanderson and O'Neill 2020). IAMs are highly complex and based on a large number of assumptions that rest on surprisingly few data observations, and this is especially true when it comes to calculating any social outcomes (T. Carleton and Greenstone 2021). IAMs attempt to translate climate effects into social outcomes, but the

underlying data observations come from the developed world, and/or a handful of sparse datasets (Drupp and Hänsel 2020).

As a result, econometricians concerned with social outcomes have increasingly studied climate effects using real world data and careful econometric measurement – rather than grand IAMs. To estimate damage functions with this approach, a 'dose response function' is modeled based on observed changes over time (Auffhammer 2018). These have been made possible by greater computing power and advances in statistical causal inference theory and have allowed economists to link rising temperatures to important social outcomes that relate directly to wellbeing, such as economic growth (Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2012), health (Deschênes and Greenstone 2011; Hutton and Menne 2014), conflicts (Hsiang, Burke, and Miguel 2013; Mach et al. 2019), agriculture (Aragón, Oteiza, and Rud 2021), migration (Cattaneo and Peri 2016) mortality (Carleton et al., n.d. 2020) crime (Burke, Hsiang, and Miguel 2015) and many others (see for example Carleton and Hsiang 2016) for a review). The limitation of this approach, however, is that the models are not very translatable to situations outside of the underlying data.

Subjective Wellbeing and Climate Change

Before discussing the importance of subjective wellbeing to climate literature, a brief introduction of SWB is warranted. SWB is often collected from a survey, and simply represents one's own evaluation of their life. It allows respondents to judge their life, based on their own observations and perceptions. Policy makers are increasingly relying on SWB measurements to complement traditional economic indicators (Estoque et al. 2019), because they offer an non-monetary gauge on the progress of raising wellbeing in society (Neve et al. 2013). SWB indicators have been incorporated in the benchmarks of an increasing number of government agencies and international organizations, such as the United Nations Development Programme Human Development Report, the OECD Better Life Index, the World Happiness Report, the U.K. Office of National Statistics or the U.S. Bureau of Labor Statistics – American Time Use Survey.

Heat is one of the most studied aspects of climate change, and Economists seem to agree that it hurts wellbeing (Carleton and Hsiang 2016). A study of 1.9 million Americans from 2008 to 2013 found that days averaging 21°C to 27°C lowered wellbeing by 1.6% of a standard deviation, and days above 32°C lowered wellbeing by 4.4%. Further, older and less educated populations are more severely affected than the rest of the population (Noelke et al. 2016). In fact, heat appears more directly related to SWB than other forms of climate change such as storms or floods (Osberghaus and Kühling 2016). Using data from 2002 to 2012, researchers 1 °C of 5-year warming associates with a 2% point increase in the prevalence of mental health issues for Americans (Obradovich et al. 2018).

The causal mechanisms are less clear. Researchers have suggested it could be due to economic costs and the inability to work (Belkin and Kouchaki 2017; Watts et al. 2019), reduced quality or quantity of sleep (Obradovich et al. 2017), the associated levels of increase in crime (Heilmann et al. 2021), or mental health issues related to high levels of air pollution and air particulates (Vergunst and Berry 2022; Younan et al. 2018). While the causal mechanisms likely vary amongst different populations, there are multiple reasons to expect a causal relationship between high temperatures and lower SWB.

However, these studies face an important limitation – they focus on weather, not climate. Weather describes short term atmospheric events, whereas 'climate' describes long term probabilistic trends observed overtime. Our paper studies climate, by considering the long-term underlying distributions of temperature.

Other studies have attempted to study the connection between SWB and temperature, but they face problems of geographic coverage and spatial precision. Their results suggest negative effects (Connolly 2013) or null effects (Feddersen, Metcalfe, and Wooden 2016; Frijters, Lalji, and Pakrashi 2020; Lucas and Lawless 2013) that in sum do not point at large effects of temperature on subjective well-being (SWB).

But these studies focus on industrialized countries (like IAMs do) where people's livelihoods are less dependent on the weather. There is now a rich evidence base showing that the burden of global warming is unequally distributed where the poor are less well equipped to cope with harmful weather events rendering them more vulnerable to temperature changes (Carleton et al., n.d. 2020; Carleton and Greenstone 2022; Diffenbaugh and Burke 2019).

By contrast the dataset used in this paper encompasses surveys from 160 countries, meaning developing countries are appropriately represented covering 13 years of sub-national data. This global dataset offers us a powerful tool to understand the relationship between the increasing number of unusually hot days and SWB.

3. Data

We merged daily temperature data with global survey data, using geolocation. The survey data came from the Gallup World Poll. The Gallup World Poll is an annual survey, conducted each year since 2006, representing 95% of the world's population each year. Each country has a sample of N=1,000, except a handful of high population countries that have larger samples, and a few small population countries which have samples of 500.

Our database contains information on 1.67 million interviews from 160 countries, from 2008 to 2020. Each respondent answered over 60 questions about their life, experiences,

perspectives, and all basic demographics. This provided a vast interview database to include in the models.

Each country is surveyed through probability-based survey methods, administering surveys through face-to-face interviews in three-fourths of the countries and phone interviews in the other quarter. For the face-to-face countries, nationally representative sampling frames are used, which are stratified by urbanity and region. Countries are sampled according to probability proportional to size sampling, and cities are not oversampled. In phone-based countries, random digit dial dual-frame landline and mobile sampling frames are utilized. The mobile/landline proportion is determined based on the country's mobile/landline usage. Base weights and post-stratification weights are usually based on the most recent census, but sometimes rely on other sources when countries have no up-to-date census. Post-stratification weights are constructed using gender, age, and education. Last, to make the World Poll data globally representative, weights were added to reflect the relative size of each country's population.

World Poll surveys are typically administered between March and October of each year, although there are several exceptions. Most interviews in our dataset were conducted in June (15%) and May (14%) and least surveys were administered in January (2%) (see summary statistics in Table 1), however, in all world regions there is quite some variations in survey months that cover all seasons of the year (see Figure 7, in the Appendix for an overview of survey month by region). Still, seasonality is an important consideration in the interpretation of the results. Countries that are experiencing winter while they are interviewed, may report a different effect size of exceptionally high temperatures, compared to a country that is experiencing summer. We address this in our global model by controlling for hemisphere specific month effects. That is, while we are not able to analyze seasonal differences in a given country, on the aggregate we can account for such seasonal differences.

Countries tend to be interviewed the same month every year, helping to ensure strong repeated cross-sectional data, but there are a few exceptions to this as well. To account for these exceptions, we control for deviations from the usual month of interview in a country. At the sub-national level, interviews are conducted in a quasi-random order throughout the region. Phone-based interviews rely on random digit dialing sampling frames, and are therefore randomized in terms of their timing and spatial coverage. For face-to-face interviews, the order varies with enumerator teams and selected sampling units and is based on travel logistics. Figure 1 depicts the distribution of the length of the data collection in each sub-national region and year (see Figure 8) in the Appendix for distributions by world region). As we discuss in more detail in the next section, we rely on the staggered data collection to identify the short-term effects of HTD in the empirical analysis.

Since 2008, the day that the interview was conducted has been recorded. This allowed us to match the temperature on the day of the interview, and each of the days preceding the interview. As discussed more later, we identify temperature 30 days before each interview. Having the date of the interview, and temperature for every day allows us to introduce variation into the dataset. For example, respondents who are interviewed at the beginning of the field period will have a different set of temperature days compared to respondents who are interviewed at the end of the field period. Most respondents, however, will share many overlapping days in the 30-day period we measure their temperature. The longer we extended the timeframe, the more days are shared between respondents, and the less variation respondents have in their temperature data. This was one consideration for focusing on a short-term timeframe of 30 days.

Temperature data was merged with the survey data using the location of the first sub-national administrative level, which are the largest sub-national boundaries, often referred to as states, provinces, departments, oblasts, etc. In total, we mapped over 3300 administrative units to enable this spatial merge. Some units cover very large surface areas, such as those in Russian Siberia or northern Canada. However, these units contain only a tiny fraction of the global population. In fact, the vast majority of the world's population lives in smaller-than-average administrative units (cities and densely populated areas were often broken into smaller units to make them more manageable). World Poll sampling is based on each location's relative population size within a given country. Therefore, most of the World Poll sample lives in administrative units with a smaller-than-average area, enabling accurate weather statistics.[1]

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[1] Gallup recorded GPS on face-to-face World Poll interviews from 2016 to 2019 in several countries. We used this subset of the data to corroborate that admin 1 areas are precise enough to measure temperature effects on well-being. For example, we replicated the main estimation model with GPS data from India and find similar results when using amin-1 or GPS based temperature matching.

Figure 1: Days interviews were conducted after start of field work in sub-national region
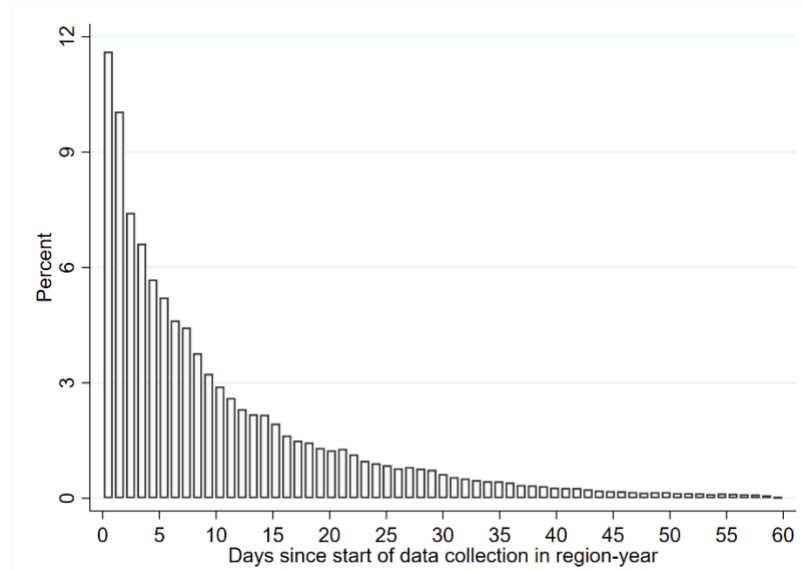
Note: Days counted in reference to start of field work in first sub-national administrative unit.

The SWB variable that serves as our dependent variable in this analysis is a Life Evaluation survey question that is based on the Cantril self-anchoring striving scale (Cantril 1965). Respondents are asked to rate their life between 0 and 10, based on what they consider the best and worst possible lives:

> "*Please imagine a ladder with steps numbered from zero at the bottom to 10 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?*

There are a few characteristics of this variable that are beneficial to our analysis. First, it is a broad umbrella variable, in which respondents take into account many factors of their life. Second, each respondent weights these factors according to what is most important in their life. These attributes are useful for our analysis because we are attempting to understand how climate impacts well-being, and the literature suggests there are a wide number of casual channels that could affect different people in different ways. Using this variable allows respondents to incorporate those factors, whether there is a known or unknown casual pathway, and establish a more accurate damage function.

The Life Evaluation question is the first item on the questionnaire for all 1.67 million interviews included in this analysis. There are a few notable trends to global SWB, as measured by the World Poll's Life Evaluation question over the past 13 years. The global mean is 5.3 (see Table 1) which has slowly dropped over the years from a high of 5.45 in the beginning of the data collection to its lowest point of 5.11 in 2019.

The World Poll's life evaluation data has been used in many academic articles and reports, such as the U.N.'s World Happiness Report. In almost every case, the data is analyzed at the national level. Being able to model the data at sub-national levels improves the precision of our analysis. The mean life evaluation of each first-administrative level of each country, averaged over the last 12 years, is shown in Figure 2. It is also clear that there is substantial variation within countries. For example, the life evaluation of the mountainous Indian state of Assam is 3.2, whereas the average in coastal Gujarat is 5.4. This 2.2 difference average life evaluation represents a substantial difference in economic development levels. It would make sense that the approaches to climate mitigation policy should be different between the two states. Therefore, it is important that climate models are based on sub-national data.

Figure 2: Mean Life Evaluation 2008 – 2020 by subnational region
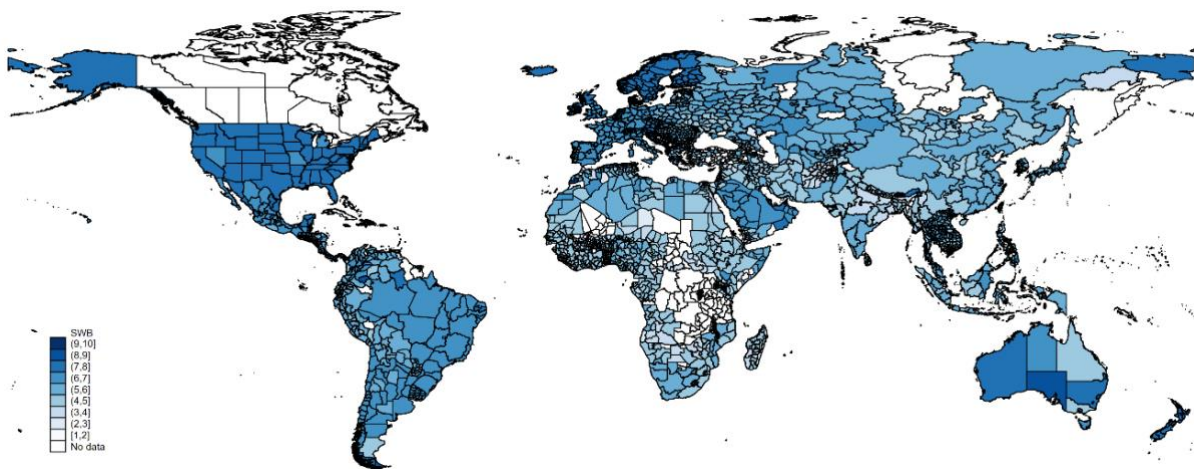
Note: regional means calculated with pooled annual data of 2008 to 2020. Life evaluation is measured on a scale 0-10.

Socio-demographic Variables

In our analysis, we compute the necessary income growth to compensate for the damage done to SWB by the increasing HTDs. Therefore, a brief description of the income variables collected is warranted. To calculate household income, the Gallup World Poll asks respondents to report their monthly household income in local currency. If respondents have trouble answering, they are presented a set of ranges in local currency and asked to which they belong. A hot deck procedure imputes these cases to determine an income within the given range. Likewise, if respondents do not answer both questions, a hot deck procedure is used to impute their income. To create comparable income variables, income data are annualized and local income is converted to international dollars using the World Bank's individual consumption ppp conversion factor, with a 2010 base.

Besides income and SWB information, the survey collects information on a number of socio-demographic information. In Table 1 we show summary statistics of all variables used in the analysis. On average, respondents are 40 years old, half are female, 47% have primary,

42% secondary, and 10% have tertiary education. About 63% are married and 53% have children. Household income is 81640 US$ and the majority reports to get by on present income or to find it difficult to get by expressed by a mean income satisfaction score of 2.3 (where a score of 1 refers to living comfortably on income and 4 refers to finding it very difficult to get by).

Table 1: Summary statistics

	N	Mean	SD	Min	Max
Subjective Well-being (SWB)	1671073	5.296	2.313	0	10
Weather indicators:					
High temperature day (day of interview)	1670401	0.034	0.182	0	1
High temperature days (15 days before interview)	1670401	0.403	1.332	0	15
High temperature days (30 days before interview)	1671073	0.791	2.228	0	30
Low temperature days (30 days before interview)	1671073	0.798	1.902	0	30
Precipitation in cm (30 days before interview)	1668243	97.559	97.757	0	1748.247
Socio-economic characteristics:					
Female	1671071	1.502	0.500	1	2
Primary education	1657037	0.473	0.499	0	1
Secondary education	1657037	0.424	0.494	0	1
Tertiary education	1657037	0.104	0.305	0	1
Single	1656934	0.268	0.443	0	1
Married	1656934	0.625	0.484	0	1
Separated	1656934	0.012	0.107	0	1
Divorced	1656934	0.023	0.149	0	1
Widowed	1656934	0.048	0.214	0	1
In partnership	1656934	0.025	0.156	0	1
Children	1656134	0.528	0.499	0	1
Age	1665743	39.807	16.923	15	101
Native citizen	1590070	0.977	0.150	0	1
Month of Interview:					
January	1671073	0.021	0.142	0	1
February	1671073	0.022	0.145	0	1
March	1671073	0.034	0.181	0	1
April	1671073	0.094	0.292	0	1
May	1671073	0.144	0.351	0	1
June	1671073	0.152	0.359	0	1
July	1671073	0.112	0.315	0	1
August	1671073	0.115	0.319	0	1
September	1671073	0.109	0.311	0	1
October	1671073	0.099	0.299	0	1
November	1671073	0.064	0.246	0	1
December	1671073	0.034	0.182	0	1

Deviation from usual month of interview	1671073	0.401	0.490	0	1
Income:					
Income ppp	1573899	8.164	249231	0	449000
Income satisfaction	1622786	2.332	0.910	1	4

Note: Population weights were used in calculation of summary statistics.

3.1 Key Temperature Variable

The temperature information was obtained from NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2)[2], a reanalysis utilizing modern hyperspectral radiance and microwave observation. This dataset contains daily temperature information, two meters above land, for the planet's entire surface, at a pixel size of about fifty by fifty kilometers. We incorporated this temperature information for every day from Jan. 1, 1980, to Dec. 31, 2020, for all land surface areas of the earth. This enabled the modeling to look at temperature changes across planet over a 14,610 day span.

To capture the number of HTD that people face, we first established an expected distribution of temperature for every sub-national geographic region by treating the days between 1980 and 2004 as our historical baseline. Next, we recorded the temperature facing respondents the day of the interview, and the 30 days prior to it. In our main definition, HTD notes the total number of days before the interview that were at least two standard deviations above the historical mean, based on the sub-national geography, based on the time of year. For example, if a respondent was surveyed in Limburg, in the Netherlands on May 31st, 2008, *hot days* represents all of the days in May 2008 that were above two standard deviations of the mean from the days in May during 1980 to 2004 in Limburg. As robustness we varied the time period and the threshold to classify HTD.

Variation to the exposure of HTDs results from a difference in when survey respondents were interviewed. Other respondents in Limburg, for example, were interviewed May 10th, meaning their 30-day temperature window included a number of different temperature records.

One limitation to this approach, however, is that over a 365 day period, the vast majority of temperature records are the same for respondents in the same region. A respondent in Limburg would experience very similar temperatures to other respondents in Limburg. Therefore, there is very little variation, when comparing them over a long period of time. There is relatively more variation in a 30-day period, because respondents are interviewed

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throughout the month. This was one reason that the hot days variable is based on a 30-day period. This allows us to analyze short-term effects very well but means that we cannot analyze long-term effects. This is a key limitation to our approach. It is very possible that the economic consequences play out over a longer period of time, and therefore we are not able to capture them using this 30-day window.

The global mean of HTDs that were experienced by respondents in 2008 was 0.35. Over the years that HTDs became more frequent and rose to 1.02 by 2020, three times as many as in 2008. It is worth noting that 2008 was a La Nina year, and cooler than average, but the data still display a large increase in HTDs in a relatively short time period as illustrated by the linear trend we overlayed on the line chart in Figure 3.

Similar to Aragón, Oteiza, and Rud (2021) and Deschênes and Greenstone (2011) we count the number of HTD before each interview. We choose to use a relative and location specific measure of HTD as opposed to using absolute temperature cut-offs to account for the region-specific difference of temperature extremes. That is, we want to regard how deviations from the historic mean affect SWB and using absolute temperatures could be confounded as countries with lower temperatures tend to be richer and report higher SWB. In addition, selecting a cut-off value would become more arbitrary than the 2 SD definition that has been used in other applications to define weather extremes (Azzarri and Signorelli 2020; Chacon Montalvan et al. 2021; Dietrich et al. 2021) However, this definition also implies that in regions with strong seasonality and high temperature variation HTD tend to be less likely to occur. For an overview of mean HTD by region, refer to Figure 9 in the Appendix.

In addition, we also identified days that were below the historical mean and generated a precipitation variable using the same spatial merging technique as the temperature data. The data comes from the U.S. National Oceanic Atmospheric Administration's Global Unified Gauge-Based Analysis of Daily Precipitation. As with HTD, the precipitation variable compares the 30 days before the interview, to the historical mean of that same period.

Figure 3: Average Number of High Temperature Days
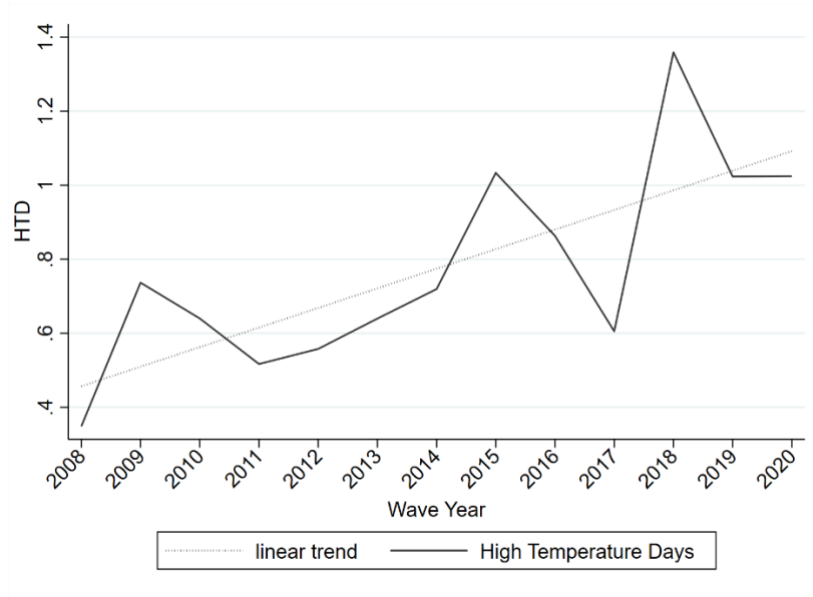
Note: Population weights used to calculate yearly means. High temperature days refer to count of days with temperatures above 2 SD of the historical mean (1980-2004) of that period and region.

4. Empirical Strategy

To estimate the impact of HTD on SWB, we explore the regional variation of the timing of interviews. We follow the standard empirical approach for studies on the socio-economic effects of climate with repeated cross-sectional data (Auffhammer 2018; Carleton and Hsiang 2016). In the main analysis we focus on the 30-days before each interview and present sensitivity tests to alternative temperature cut-offs and recall periods as an extension. We start with a simple OLS model to estimate the average effect of high temperature days on subjective well-being:

$$SWB_{ir} = \beta_0 + \beta_1 HTDs_{ir} + \beta_2 HTD_{ir}^2 + \beta_3 \, cold \, days_{ir} + \beta_4 precipitation_{ir} + \beta_5 \boldsymbol{C} + \vartheta t + \omega r + \epsilon_i \quad (1)$$

Where SWB_{ir} refers to the life evaluation of respondent i in region r and HTD refers to the number of high temperature days 30 days prior to the interview. To allow for nonlinear effects we use a quadratic term of HTD besides the linear term.[3] We additionally include the number of cold days and precipitation anomalies but focus in the discussion on high temperature days. Furthermore, we control for a vector of respondent characteristics as shown in Table 1 (except for income variables). To ensure that other region and time specific omitted variables do not confound the analysis, we gradually expand a system of time and region fixed effects that we

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[3] We also tested the main models with additional cubic terms, which were not statistically significant.

refer to as t and r in equation 1. The full model contains region-year, and month-hemisphere fixed effects as well as controls for country specific time trends and deviations from the usual month of interview in a country.

In the fully expanded specification, we explore the variation in HTD among respondents in the same region-year to estimate the average effect of a unit increase in *hot days*. Thus, we compare SWB of respondents in the same region and year who were differently exposed to high temperatures. Variation in the exposure to HTD in this model originates from differences in the timing of interviews, which explains the focus on the near-term effects i.e., the 30 days before the interview in the main analysis.

Despite the discrete and censored distribution of SWB we use OLS models as has been done in other research on SWB (see for example Maddison, Rehdanz, and Welsch 2020 for an overview) which is computationally easier given the large number of observations and covariates and validate the results using generalized linear models that account for the censored and discrete dependent variable. In the main model we cluster standard errors at the district-year level, the level at which our key variable of interest varies.

5. Results

We focus the discussion of the results on the predicted effect of a unit increase in HTD holding all else constant at observed values. For complete estimation results we refer to the Appendix. Estimates of the marginal effects are presented in Table 2. We start with a sparse model and gradually expand the number of fixed effects included.

The model of column 1 includes country-year fixed effects and national trends. The marginal effect estimate is negative, however, not statistically significant. While the model accounts for national trends and country fixed effects, especially in large countries omitted local factors could bias the estimates. In column 2, we include sub-national year-specific fixed effects, the most granular geographic information available for all data waves to the model. The magnitude of the marginal effect increases compared to the previous estimate and turns highly statistically significant. The coefficient suggests that an additional HTD reduces SWB by about 0.036 points holding all else constant at observed values. This may sound little, but it implies that a single additional high temperature day reduces SWB by more than 0.5% in the global model. Adding additional fixed effects to account for month and region-specific effects as well as country trends does not change this finding (column 3).[4]

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[4] The effect is also robust to clustering standard errors at the country level instead of the region-year level and to using a censored generalized liner model with a poisson link function that accounts for the discrete distribution of the SWB variable (like model of column 3 only considering observations which are not negative after fixed effects mean transformation; marginal effects: -0.025 glm vs -0.012 OLS).

Often high temperature days occur as part of heat waves that extend over several days. In column 4, we use a binary indicator that measures the occurrence of high temperature days instead of the count of days. The results show an even stronger effect of -0.086 if at least one HTD occurred 30 days prior to the interview. It suggests that the effect on the extensive margin is more impactful than on the intensive margin.

In addition, we test how applying less extreme definitions of high temperature days affects results. In column 6 and 7 we use 1.5 SD and 1 SD from the mean instead of the 2 SD as cut-off to classify HTD. The coefficients half in magnitude if a cut-off value of 1.5 SD is used and even turn statistically insignificant for the 1 SD definition. This implies that the effects are driven by the occurrence of particularly extreme temperature days.

Furthermore, we test whether the effect changes over time for example because of successful adaptation to increasing temperatures. In column 8, we show the effect for the subset of the data collected in the years 2015 through 2020 which represents approximately half of the dataset. The predicted marginal effect of -0.034 is not statistically different from the overall marginal effect estimate of -0.036 suggesting that effects have not decreased compared to earlier years in the database. This result also holds if we use shorter time periods or year specific predictions, which does not point at noteworthy adaptation processes in the global data.

Next, we examine differences in effects between respondents that were interviewed in the beginning of the regional field work (first 25%) or the end (last 25%). Respondents that were interviewed later were exposed to the same HTDs as early respondents just that they happened further in the past. In contrast, late respondents can be exposed to HTD that occurred after early respondents were already interviewed. Therefore, if respondents do not or only slowly recover from HTDs, we would expect the HTD effect to be larger for late respondents. However, the results of column 8 do not show significant differences in effects, which could point at fast recovery processes in SWB after temperature extremes occurred. This finding also holds if we only focus on regions in which the field work lasted for at least 30 days.

In the main results we use a recall period of 30 days to quantify the short-term effects of high temperature days. A mid- or long-term evaluation perspective is complicated because identification relies on variation in the timing of interviews. To better understand the temporal dynamics, we re-estimate the model using different recall periods. The effect of a HTD on the day of the interview has a negative sign but is not statistically significant (column 8). It turns significant for the period from 1 to 15 days and further increases for the period from 16 to 30 days before the interview.

These results seem to suggest that the negative effects do not unfold immediately. What is driving the negative effects then? Conceptually different mechanisms could be at play

including income or wealth effects because of high temperatures (e.g. reduced productivity), health effects (e.g. cardiovascular, respiratory disease, or cerebrovascular diseases), or belief updates regarding future states of the world (e.g. less optimism because of experienced signs of global warming (Coffey et al. 2021). To get a sense of possible drivers of the impact, we estimate the effects of HTD on proxy indictors for wealth (income), health (subjective health problems), and SWB in 5 years (see Table 6 in the Appendix). The results show a negative income effect of HTD on the day of the interview that subsides after 15 and 30 days after the interview, no health effects, and negative effects on expected future wellbeing. This result could suggest that income effects occur in the short-term, which may contribute to less optimistic views about well-being in the future and that the global impacts are not significantly driven by health effects.

To account for contextual differences, we consider effect differences by geographical region. In Table 7**Error! Reference source not found.** in the Appendix we present estimates by world regions. The results indicate that the global estimate is driven by negative effects in South and East Asia where we find effects sizes of -0.132 and -0.062 respectively. Effects in Latin America, the MENA region, Sub-Saharan Africa, and Commonwealth states reach about -0.03 but fail the 5% significance level and we find no effects in Europe. North America, and Australia. What explains these regional differences? One explanation is that we use a relative measure that depends on the variation of temperatures in the region. In regions with large temperature variation because of seasonality or weather phenomena such as the monsoon, HTD require a larger increase in absolute temperature than in regions with less temperature variation. That is, in South Asia the impact of an additional HTD is large, but at the same time HTDs are less likely to occur compared with other regions (see spatial distribution of HTDs in **Error! Reference source not found.**in the Appendix).

In addition to world regions, we also separately estimate effects by age, gender, and wealth of respondents (see Table in the Appendix). We find that respondents older than 65 are more strongly affected then younger respondents and richer respondents (rich within countries) are more strongly affected in absolute terms but not in relative terms, and we find no gender differences on average. Breaking these estimates further down by world region shows, that mechanisms differ, and the effects depend on the context. Yet, the result indicate that effects are largest in lower- and upper-middle income countries. Respondents in richer countries seem, on average, to be less affected by the occurrence of high temperature days. As, high income countries are more likely to be found in cooler regions, we also tested for differential effects by countries were HTD were more like to occur (more than 15 days above 35 degree per year). Effects of HTD are larger in hotter (0.053) than in colder (0.031) countries but the difference is not statistically significant. More generally, we observe that effects are driven by

temperature extremes in hotter months. The effect of HTD is about twice as large if it happens in the hottest months of the world region as compared to other months with marginal effect estimates of -0.066 compared with -0.033 respectively (see Table 7 in the Appendix).

In summary, we find a statically significant effect of HTD on subjective well-being that does require some time to fully unfold, but at the same time does not last much beyond the usual field data collection period of around one month. The effect is driven by respondents in poorer countries and by temperature extremes in generally hotter months. Whether and how economically meaningful these effects are is subject of the next section.

Table 2 Marginal effect of additional hot day on SWB

	(1) 30 days	(2) 30 days	(3) 30 days	(4) 30 days	(5) 30 days	(6) 30 days	(7) 30 days	(8) 30 days	(9) Day Interview	(10) 1-15 days	(11) 16-30 days
Additional hot day (2SD)	-0.013 (0.009)	-0.036** (0.008)	-0.037** (0.008)								
Hot day (binary)				-0.086** (0.026)							
Additional hot day (1.5SD)					-0.017* (0.005)						
Additional hot day (1SD)						-0.003 (0.005)					
Years 2015-2020							-0.034** (0.011)				
Hot day (first 25%) (beginning of field work)								-0.047** (0.014)	-0.084 (0.062)	-0.024 (0.026)	-0.102** (0.030)
Hot day (last 25%) (end of field work)								-0.060** (0.016)	-0.067 (0.069)	-0.068** (0.022)	-0.093** (0.031)
Respondent Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country-Year FE	yes	no	no	no	no	no	no	no	no	no	no
Region-Year FE	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month-Hemisphere FE	yes	no	yes	no	no	no	no	no	no	no	no
Year*Country trend	yes	no	yes	no	no	no	no	no	no	no	no

Note: Predicted marginal effects based on OLS model with SWB as dependent variable. Standard errors clustered at region-year level in parentheses. Controls include age, age^2, age^3, sex, marital status, education, children, deviation from survey month from the usual in region. Number of Observations in the first model is 1549450. First and last 25% is used to classify beginning and end of field work in in each region-year (therefore only half the data is used in models 8-11).

* $p < 0.05$. ** $p < 0.01$

6. Mechanisms and cost of rising HTD

The results give an idea of how the increasing occurrence of temperature extremes affects well-being in the short run. Building effective policy interventions to manage the climate crisis requires monetizing these damages. However, missing price signals of non-market goods make it particularly difficult to monetize them. A range of environmental economic papers use SWB measures to value environmental public goods using an experienced utility approach (Luechinger 2009; Luechinger and Raschky 2009; Ren, and Folmer 2020; van Hoorn 2018). The underlying idea of this approach is to compute the marginal rate of substitution between the marginal utility of income and the marginal utility of the environmental good, where utility is approximated by SWB reports. Consequently, the marginal benefits and costs of a non-market good can be estimated with SWB data. In this section, we apply the approach to compute the income increase necessary to compensate for the SWB damage caused by HTD. In a second step, we extrapolate based on the data the expected HTD in the coming decade, which we then use to calculate the income growth necessary to compensate for the damage related to the projected increases in HTD.

Income versus non-income effect mechanisms

To quantify the costs, we need to understand the income and non-income damage caused by HTD. To this end, we fit a linear structural equation model as displayed in Figure 4. HTD is the main exogenous variable in the model that affects respondents' income for example through production losses (1). Changes in income in turn affect SWB, as has been widely established in the literature (Diener and Oishi 2018; Stevenson and Wolfers 2013, Diego et al 2018) (2). We refer to this path as the income effect (1*2). As the effect of income on SWB is not linear and has been found to rather follow a logarithmic function (Deaton 2008; Stevenson and Wolfers 2013) we log-transform income reports.[5] The non-income mechanism is the collection of all other effects that are not captured by the income effect (3). This may include health effects, stress, psychological effects, or social conflicts just to mention a few. The linear model includes the same control variables as the model in column 3 of Table 2 **Marginal effect of additional hot day on SWB**. except that the second equation of the income effect path also includes respondent's income.

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[5] About 2% of respondents report 0 income which are treated as missing values after the log-transformation. Replacing 0 income reports with small positive values does not change the results markedly. Moreover, removing imputed income reports also does not change results substantially.

Figure 4: Structural model outline
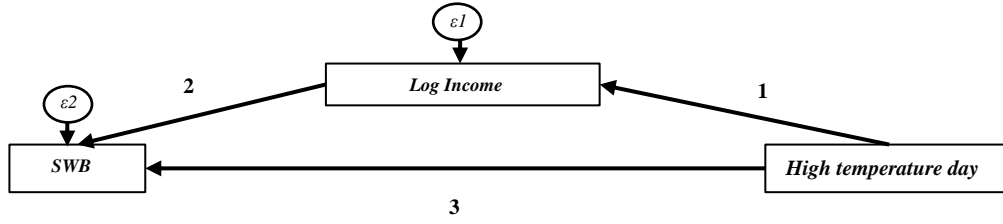
The predicted marginal effects are presented in Table 3 and the complete estimation results are shown in Table 5 in the Appendix. In the global model, most of the effect of HTD on SWB is explained by non-income effects, and only less than 5% of the non-income effect, is related to income changes. This is because HTD only have a small effect on incomes, at least in the 30-day period considered here, which despite the very strong effect of incomes on SWB only leads to a small income effect. The point estimate of the non-income effect is almost identical to the previous estimates, which suggests that the short-run effect is dominated by non-income aspects.

A shortcoming of this approach is the short-term focus and that the negative income effects of HTD may not unfold immediately. For example, if heat damages a farmer's crops, the income effect may not manifest until later in the year. As a robustness test, we use respondents' income satisfaction which we regard as a broader measure that may also encompass expected future incomes (see results in Table in the Appendix). The income effect increases markedly if we use income satisfaction instead of income and reaches about 29% of the non-income effect in the global model. We regard this as an indication that expected incomes and a more long-term perspective would increase the weight of the income effect mechanism markedly, however, non-income effects remain the dominant mechanism.

Based on the structural model estimates we can compute the income increase necessary to compensate for the SWB damage of an additional HTD. The compensation needs to cover the income damage of HTD plus the income increase to compensate for the non-income effect. As we log transformed incomes, we interpret the compensation as an approximation of percentage changes in incomes. In column 4 of Table 3 we present the average income increase needed to compensate for an additional HTD. According to the global model, it requires an 8.8% increase in income to compensate for the damage of an additional HTD holding all else constant at observed values. This constitutes a substantial increase and helps to put the main results into perspective.

As expected, the results differ largely by world region. In the lower part of Table 3 we show the estimates separately by world region. The non-income effect is largest in South Asia

(-0.136) and the income effect is largest in the MENA region. The effect of income on SWB is lowest in Sub Saharan Africa and largest in non-E.U. Europe. Combining those numbers, South Asia shows by far the largest 'cost' of a HTD with 26.9% of income followed by East Asia, Sub Saharan Africa and Latin America. On the other end, in Australia and Southeast Asia signs are even negative. These numbers illustrate the large discrepancy in damages that has also been found in other studies. For example, climate change is expected to increase the overall global mortality rate (Carleton et al. 2020). But it is expected to decrease the mortality rate for northern latitudes, starting at roughly the 45th parallel.

Table 3: Marginal effect of HTD on income and SWB

	(1) HTD -> Income	(2) Income -> SWB	(3) Non-Income	HTD cost of income
Global	-0.003	0.410	-0.035	8.8%
E.U.	-0.004	0.512	-0.013	2.9%
Rest Europe	-0.016	0.553	0.010	0.2%
Commonwealth	-0.004	0.437	-0.030	7.3%
Australia	0.005	0.344	0.009	-3.1%
Southeast Asia	-0.002	0.347	0.013	-3.5%
South Asia	0.013	0.483	-0.136	26.9%
East Asia	-0.016	0.487	-0.058	13.5%
Latin America	0.002	0.334	-0.030	8.8%
North America	0.012	0.262	-0.011	3%
Mena	-0.011	0.420	-0.015	4.7%
Sub Saharan Africa	-0.010	0.227	-0.021	10.3%

Linear structural equation model as illustrated in Figure 4 including fixed effects as in model 3 of Table 2. Estimates show marginal effects at observed values and complete estimation output can be found in Table 5. HTD cost of income show approximated income growth to compensate for HTD damage (1+(3/2)*100).

Subjective Wellbeing Damages resulting from rising temperatures

In the last step we use the estimates to project the income growth that will be necessary to compensate for the rising frequency in HTD. Therefore, we use a simple linear trend as shown in Figure 3 to extrapolate the increase in HTD. Slightly more sophisticated models that better capture non-linear functional forms led to similar results, but it is important to note that our goal with this exercise is not to provide the most accurate forecasts of HTD but to illustrate the damage magnitude that such changes may cause and how the damage is distributed. We use these estimated trends to predict HTD for each year and region for the years 2021 until 2030 and given the model simplicity refrain from doing more long-term projections. Thereafter we feed the predicted HTD into the structural model to simulate the SWB damage caused by the projected changes in HTD. We calibrate the model with data of 2019 the latest survey before the pandemic. In other words, we predict how SWB changes if HTD increase

holding all else constant at 2019 values and compute by how much incomes will need to grow to offset the SWB damage considering the income and non-income effect mechanisms.[6]

Figure 5 shows the results of the global model indicating that compared with 2019, it will require a growth of almost 4% in incomes by 2030 to compensate for the increase in HTD. The growth rates increase by about 0.4 percentage points yearly and the rates only marginal subdues over time due to small decreasing marginal damage of an additional HTD. Using slightly more flexible functional forms to model the growing increase in HTD increases the effect. For example, using a quadratic function form instead of a linear trend increases the compensating growth to more than 5%.

Figure 5: Income growth to compensate for HTD damage compared with 2019
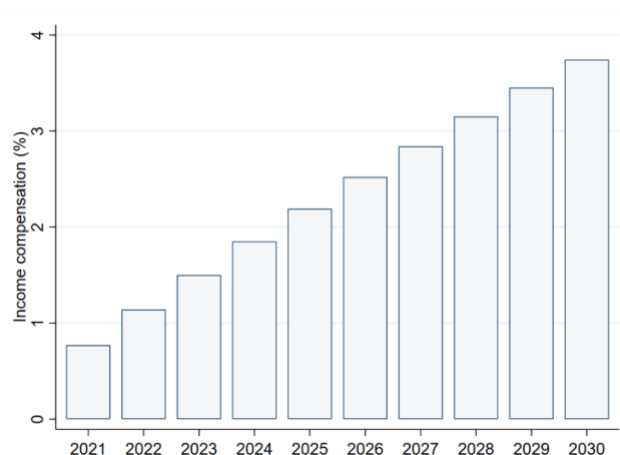

Note: Income growth necessary to compensate for income and non-income damage of projected increase in HTD compared with 2019. Damage estimates based on the results of the global structural equation model. Increase in HTD extrapolated with region specific linear trend from 2008 to 2019. Mean compensation rates calculated using population weights.

The average compensation rates are high, but previous results suggest that they are unequally distributed. In the last step we compute regional compensation rates by allowing HTD trends and SWB effects to differ regionally. We map the compensation in Figure 6. The darker the shade of red, the larger the income growth necessary to compensate for the projected SWB damage. The map clearly shows that poorer countries require disproportional growth rates than richer countries. While most high-income countries have estimated compensation rates close or even slightly below zero, rates in Sub-Saharan Africa, South and Southeast Asia exceed 10%. With the previous results in mind, it may look surprising to see largest rate in Sub-Saharan African countries compared with India where we saw the largest marginal damage, but this is again mainly explained by two components. First, HTD are rather uncommon and more unlikely to occur in India than in many other regions possibly related to

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[6] Therefore countries that were not surveyed in 2019 are not part of this simulation exercise.

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the large standard deviation in temperatures. This makes the marginal damage quite large but also quite unlikely. Secondly, in Sub-Saharan Africa it requires the largest increase in income to compensate for a unit reduction in SWB. That is, in our framework the 'price' for changes in SWB is about twice as high as in South Asia. To illustrate these underlying mechanisms we show the projected change in HTD and the predicted SWB damage by world region in Figure 12 and Figure 13 Appendix.

Figure 6: Income increase to compensate for SWB damage of increasing HTD in 2030 compared with 2019
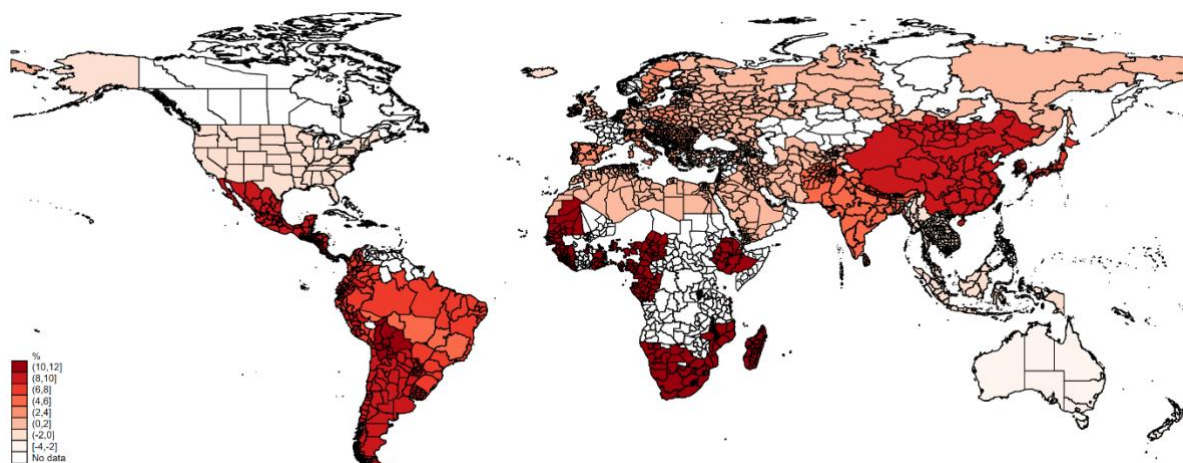
Note: Predictions based on region specific linear projections of HTD changes from 2019 to 2030 and world region specific estimates of the structural equation models.

7. Discussion

Ultimately our results help confirm assumptions inferred by previous, more geographically limited studies. Indeed, extreme temperatures measurably lower people's wellbeing in most countries across the world. However, the effect size varies substantially between and within countries. IAM models that make sweeping assumptions about global impacts should be revised to better incorporate the large differences in climate impacts around the world.

IAMs should also be advised to better incorporate non-market goods. Our results show that in fact, the majority of the damages from rising temperatures affect people through non-market channels. These channels should be further investigated and deserve more attention in current climate econometric modeling. Our experienced utility approach used to monetize this damage estimates a growth of 4% in incomes will be necessary by 2030 in order to compensate for the increase in HTD. While not directly comparable, this estimate is greater than estimated GDP damages from recent climate change reports. Last year, the Swiss Re Institute estimated global GPD loss between 5% and 14% by the year 2050 depending on whether temperatures remained below 2°C or rose to 2.8°C respectively ("Swiss-Re-Institute-Expertise-Publication-Economics-of-Climate-Change.Pdf" n.d. 2022)

Although our analysis shows the rough magnitude of effects over the rest of the decade, it is important to note that this does not imply that continuous GDP growth will compensate for all HTD damages in the future. There are multiple reasons for this. First, this analysis treats HTD as exogenous. However, literature has long established a connection where GDP growth leads to more CO2 emissions (Tucker 1995). If countries simply push for ever greater GDP growth to compensate for SWB damages, that GDP growth will lead to an increase in CO2 emissions, which in turn, will lead to greater climate and HTD damages. This raises a second consideration, income is not a perfect substitute for SWB. While most studies show that income is the largest factor in SWB, it is only one of many factors and has diminishing marginal benefits to SWB (Kahneman and Deaton 2010). For example, increasing HTD could lead to adverse health outcomes and mortality rates, which no increase in income would compensate for. Lastly, it should be noted that we present point estimates of results that are uncertain and in some regions the damage estimates fail statistical significance. More precise, geo-localized SWB data collected over time would help improve the accuracy of these estimates.

Perhaps more important than the exact size of the estimated losses is our finding that income only makes up a small share of the total HTD damage on SWB. It is possible that this underestimates the income effect size because of the short-term nature of the temperature variable (only 30 days long). Nonetheless, it presents evidence that climate change is affecting people through many non-income pathways that are unaccounted for. This suggests that the income-oriented economic valuations of climate related welfare damages functions are potentially missing key variables, and that highly utilized and impactful policy instruments like the Social Cost of Carbon and carbon emissions markets substantially undervalue climate-related damages. Perhaps this partially explains why the weighted average of these carbon pricing instruments remains insufficient to keep global temperature from rising 2°C (Watts et al. 2019). Carbon is priced at only US$1/ton CO2e (tCO2e) by the Polish Government, and the Chongqing and Shenzhen pilot schemes in China, but is priced at $127/tCO2e in Sweden, who uses a different calculation.

Climate Change's monetary impact is one way in which its damages have been communicated for decades, but as psychologists are increasingly showing, there are many non-monetary effects of climate change. Thus, including a subjective measure of those effects should be considered in new approaches to measure climate change damages. Including subjective measures in carbon pricing could improve the price discovering process, more accurately value carbon emissions, and lead to more appropriate policy responses.

Our projection model does not take into account the ability of populations to adapt to rising temperatures. Adaptation is an important consideration in climate econometrics models, and

not including it can lead to an overestimation of damages to social outcomes. Evidence suggests that populations who experience repeated extreme climate events learn to mitigate against its damages. For example, countries hit by typhoons more often report less adverse marginal GDP effects than those hit less frequently (Hsiang, 2014). Estimated mortality impacts from climate change that do not take into account adaptation tend to overestimate impacts by a factor of 2.6 (Carleton et al, 2020). However, adaptation is difficult to quantify as it is largely unobservable. Also, the local population needs to pay for these adaptations, so it is important to take their costs into account. These costs can be substantial, they are projected to rise over time, and may be unaffordable to lower-income populations. In our global model, we find that the effect size of HTD is largely the same from 2015 to 2020 as it is for the rest of the period of observation. This suggests that people have not made a substantial improvement in their ability to adapt to HTD on a global level in the past, because we do not see a reduction in the HTD effect. Still, further research in this area should incorporate adaptation models to more accurately predict the future effects sizes on SWB.

Overall, this paper makes several contributions to the literature. It analyzes one of the most globally comprehensive models, providing useful insight into the differences between high-income and low-income regions of the world. It demonstrates the substantial variation of effects of rising temperatures on SWB at sub-national levels as well, illustrating the importance of taking local conditions into account in any climate econometric models. Using novel methods, the paper quantifies the welfare damage of global warming's effects around the world and is able to disentangle the income effects and non-income effects, showing, at least in the short run, the non-income effects are much higher that what is assumed in current models. It provides strong evidence that the current policy tools, such as the Social Cost of Carbon, underestimate the damage that climate change is having on social outcomes.

Often the debate of climate policy is framed as a tradeoff between economic gains and environmental regulation. However, by monetizing the SWB damages, we see that the climate damages to society are mounting, making the economic growth required to compensate for SWB losses increasingly high and harder to obtain. The cost and benefit analysis that policymakers need to make around the world when evaluating environmental impacts, is becoming increasingly tipped toward the side of environmental protection. This research, and future research utilizing these methods, can help policymakers understand the nuanced effect climate change has on a wide number of non-market goods, across different geographies and populations. It suggests that subjective measures could be a very powerful addition to climate impact models.

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9. Appendix – Tables and Figures

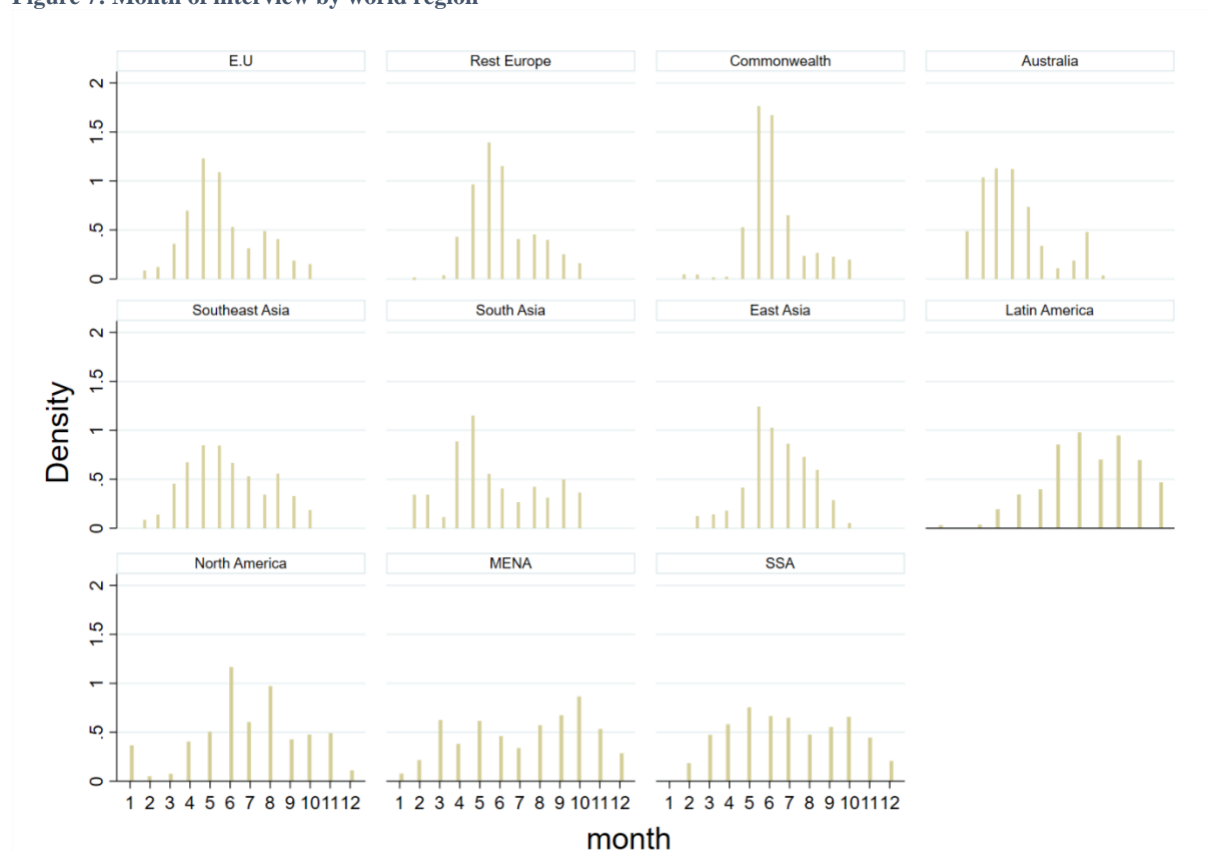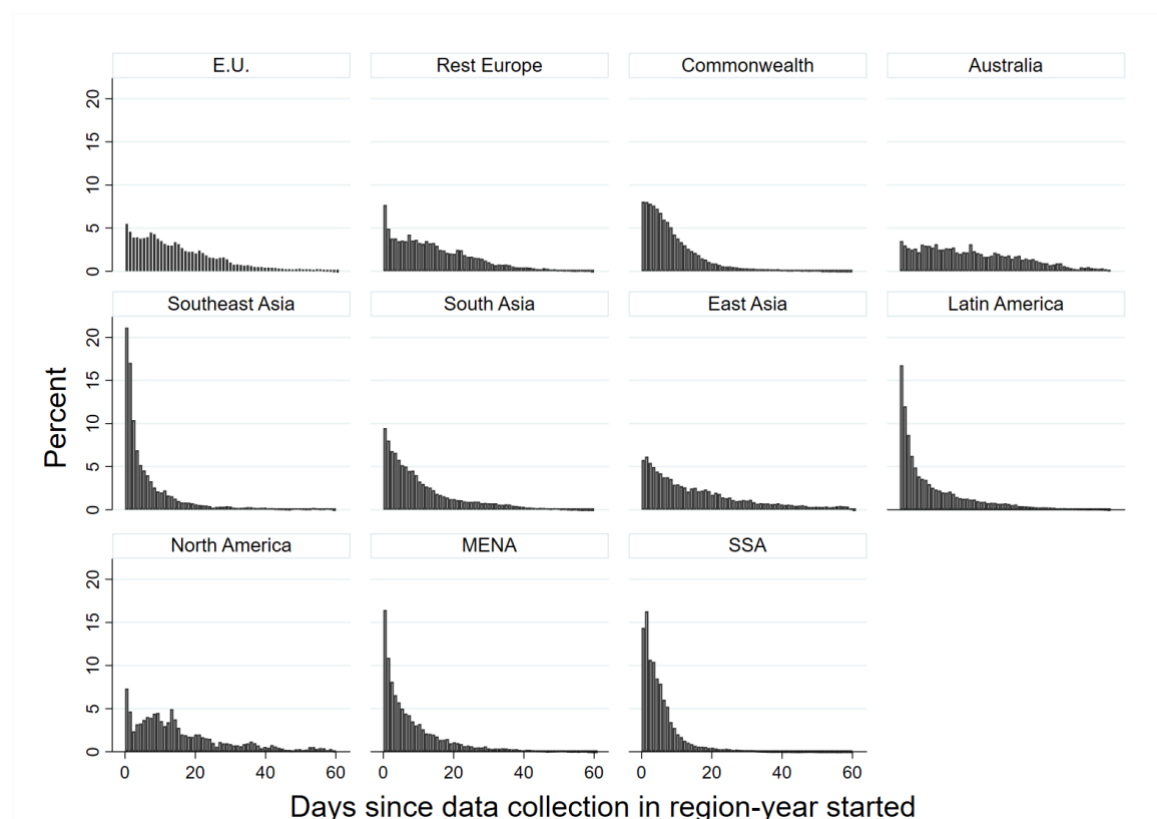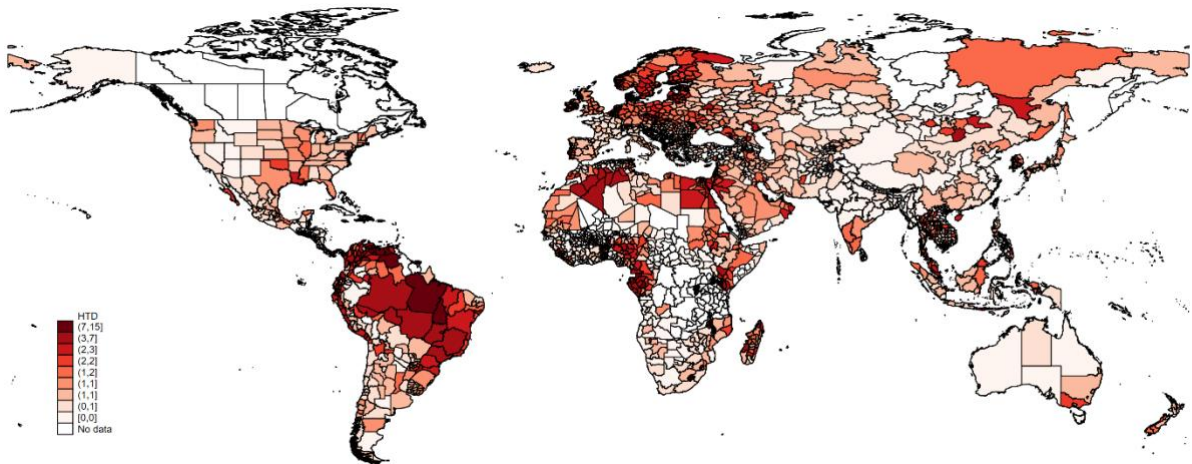**Figure 7: Month of interview by world region**

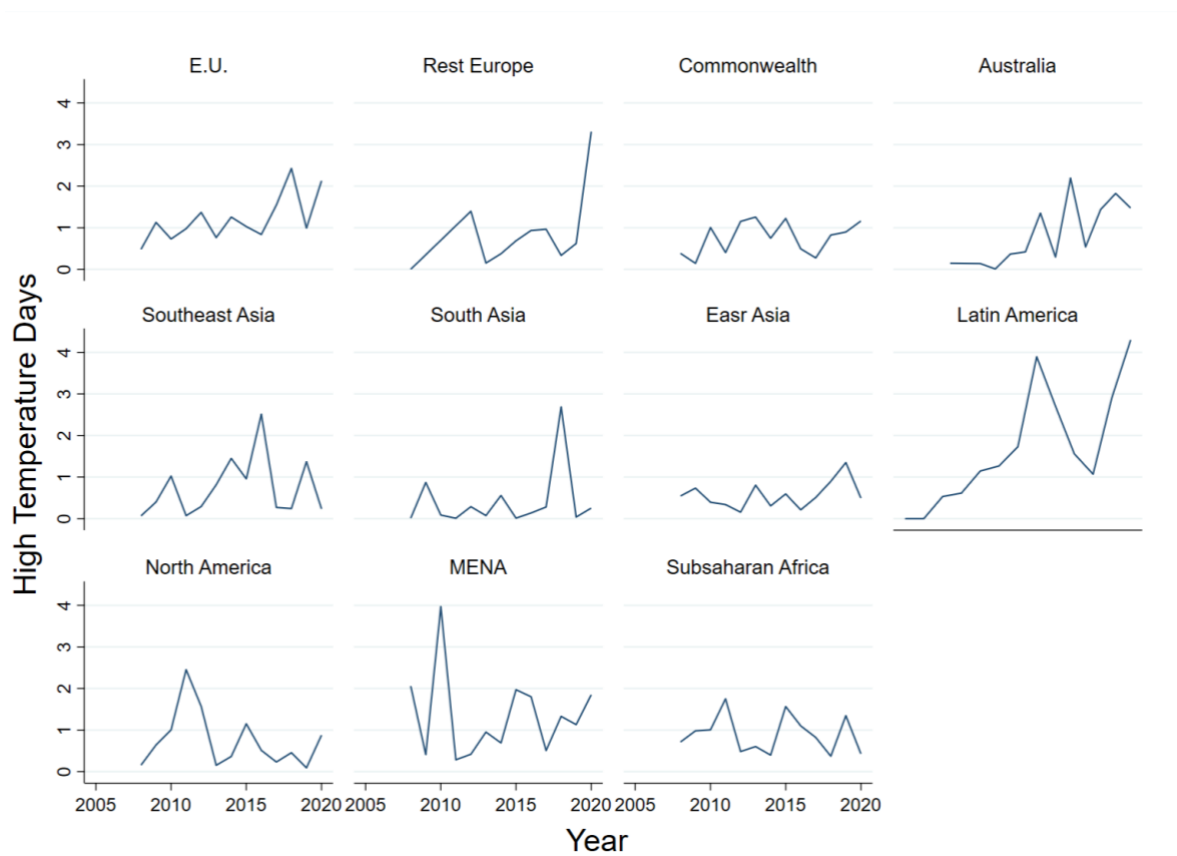**Figure 8: Length of data collection in district-year by world region**

Figure 9: Mean HTD by region

Note: region means calculated with pooled data 2008-2020.

Figure 10: HTD 30 before interview by world region and survey year

Note: world region - year means calculated using population weights. HTD refer to period 30 days prior to interview

Table 4: Complete estimation results *(Table 2)*

	(1) Life Today	(2) Life Today	(3) Life Today	(4) Life Today	(5) Life Today	(7) Life Today
HTD	-0.015	-0.040**	-0.041**			
	(0.010)	(0.009)	(0.009)			
HTD sq.	0.001*	0.002**	0.003**			
	(0.001)	(0.001)	(0.000)			
Cold temp. day	-0.009	-0.008	-0.003	-0.008	-0.009	-0.008
	(0.014)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
precip_30_prior	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	0.152***	0.138**	0.138**	0.138**	0.138**	0.138**
	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Secondary	0.571***	0.481**	0.482**	0.481**	0.481**	0.481**
	(0.017)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Tertiary	1.117***	1.016**	1.016**	1.016**	1.016**	1.016**
	(0.022)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Married	0.208***	0.191**	0.190**	0.191**	0.191**	0.191**
	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Separated	-0.231***	-0.251**	-0.251**	-0.251**	-0.251**	-0.251**
	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Divorced	-0.287***	-0.308**	-0.308**	-0.308**	-0.308**	-0.309**
	(0.032)	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)
Widowed	-0.138***	-0.135**	-0.136**	-0.135**	-0.135**	-0.135**
	(0.030)	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)
Domestic partnership	-0.011	-0.011	-0.011	-0.010	-0.010	-0.010
	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
children	-0.093***	-0.013	-0.013	-0.013	-0.013	-0.013
	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	-0.105***	-0.118**	-0.118**	-0.118**	-0.118**	-0.118**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age # Age	0.002***	0.002**	0.002**	0.002**	0.002**	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age # Age # Age	-0.000***	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
native	0.175***	0.179**	0.181**	0.179**	0.180**	0.180**
	(0.027)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
month_dev	0.040	0.035	0.070	0.035	0.034	0.035
	(0.041)	(0.041)	(0.039)	(0.041)	(0.041)	(0.041)
Binary HTD				-0.086**		
				(0.026)		
HTD (1.5 SD)					-0.020*	
					(0.007)	
HTD (1.5 SD) sq.					0.001	
					(0.001)	
HTD (1 SD)						-0.000
						(0.008)
HTD (1 SD) sq.						-0.000
						(0.000)
N	1549450	1549363	1549363	1549363	1549363	1549363
Country-Year FE	yes	no	no	no	no	no
Region-Year FE	no	yes	yes	yes	yes	yes
Month-Hemisphere FE	yes	no	yes	no	no	no
Year*Country trend	yes	no	yes	no	no	no
Year*Country trend	no	yes	no	no	yes	yes

Standard errors in parentheses clustered at region-year level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Complete estimation results (structural model)

	(Global)	(E.U.)	(Europe)	(Common)	(A)	(SA	(SEA)	(E|A)	(LA)	(NA)	(MENA)	(SSA)
	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome	lnincome
Ln income												
HTD sq.	0.000	0.001	0.002*	0.002	-0.002	-0.001	-0.000	0.002	-0.001	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
HTD	-0.004	-0.005	-0.020	-0.006	0.009	0.002	0.014	-0.020	0.003	0.015	-0.013	-0.011
	(0.007)	(0.005)	(0.011)	(0.009)	(0.015)	(0.018)	(0.012)	(0.022)	(0.006)	(0.025)	(0.008)	(0.013)
Cold day	-0.000	-0.006*	0.017	-0.015**	0.018*	-0.002	-0.005	0.025	0.003	-0.021	0.006	-0.004
	(0.006)	(0.003)	(0.011)	(0.006)	(0.007)	(0.010)	(0.010)	(0.013)	(0.011)	(0.028)	(0.007)	(0.012)
precip_30_pr	-0.000	0.000	0.000	0.000	-0.000	-0.001***	-0.000	-0.000	-0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Gender	-0.071***	-0.113***	-0.040**	-0.073***	-0.137***	-0.077***	-0.015	-0.045***	-0.185***	-0.192***	-0.060***	-0.091***
	(0.004)	(0.006)	(0.013)	(0.007)	(0.019)	(0.013)	(0.009)	(0.010)	(0.009)	(0.028)	(0.008)	(0.010)
Secondary	0.243***	0.202***	0.219***	0.082***	0.245***	0.301***	0.301***	0.366***	0.369***	0.476***	0.248***	0.265***
	(0.007)	(0.009)	(0.014)	(0.011)	(0.040)	(0.014)	(0.012)	(0.016)	(0.010)	(0.082)	(0.010)	(0.010)
Tertiary	0.632***	0.537***	0.456***	0.349***	0.657***	0.744***	0.722***	0.655***	0.927***	1.058***	0.613***	0.840***
	(0.009)	(0.010)	(0.016)	(0.012)	(0.043)	(0.022)	(0.021)	(0.025)	(0.018)	(0.082)	(0.013)	(0.023)
Married	0.177***	0.031***	-0.097***	0.003	0.315***	0.207***	0.083***	0.250***	0.131***	0.278***	0.063***	0.153***
	(0.008)	(0.009)	(0.026)	(0.011)	(0.030)	(0.020)	(0.012)	(0.021)	(0.011)	(0.035)	(0.011)	(0.012)
Separated	0.076***	0.144***	-0.098	0.040	0.062	0.215***	0.134*	0.260*	0.114***	-0.167	0.020	0.042
	(0.017)	(0.021)	(0.054)	(0.022)	(0.057)	(0.046)	(0.061)	(0.114)	(0.019)	(0.095)	(0.055)	(0.033)
Divorced	0.081***	0.054***	0.006	0.001	0.201***	0.254***	0.099	0.207***	0.228***	0.090	0.116***	0.120***
	(0.015)	(0.014)	(0.034)	(0.015)	(0.043)	(0.054)	(0.086)	(0.047)	(0.025)	(0.053)	(0.026)	(0.031)
Widowed	0.215***	0.128***	0.090*	0.014	0.287***	0.246***	0.119***	0.331***	0.222***	0.242***	0.129***	0.120***
	(0.013)	(0.013)	(0.036)	(0.016)	(0.043)	(0.031)	(0.023)	(0.044)	(0.019)	(0.058)	(0.026)	(0.024)
Domestic partnership	0.011	0.075***	-0.064	-0.042	0.362***	0.087	-0.092	0.115	0.035**	0.332***	0.199*	0.081***
	(0.010)	(0.012)	(0.034)	(0.023)	(0.047)	(0.046)	(0.165)	(0.087)	(0.013)	(0.070)	(0.094)	(0.020)
children	-0.519***	-0.466***	-0.476***	-0.465***	-0.530***	-0.477***	-0.451***	-0.465***	-0.602***	-0.656***	-0.453***	-0.831***
	(0.007)	(0.007)	(0.015)	(0.008)	(0.024)	(0.012)	(0.012)	(0.017)	(0.010)	(0.035)	(0.010)	(0.014)
Age	-0.004***	0.001***	0.002**	-0.003***	-0.006***	-0.004***	0.001	-0.013***	0.002***	0.003**	0.000	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
native	0.270***	0.177***	0.108***	-0.000	0.119***	0.180	-0.091	0.035	0.083*	0.270***	0.265***	-0.095***
	(0.015)	(0.012)	(0.032)	(0.015)	(0.021)	(0.113)	(0.047)	(0.084)	(0.034)	(0.041)	(0.021)	(0.025)
month_dev	0.023	-0.004	-0.015	0.018	-0.012	-0.002	0.014	0.022	0.016	0.017	0.011	-0.027
	(0.020)	(0.014)	(0.026)	(0.022)	(0.034)	(0.030)	(0.054)	(0.041)	(0.032)	(0.041)	(0.019)	(0.051)

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SWB

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
lnincome	0.410***	0.512***	0.553***	0.437***	0.344***	0.347***	0.483***	0.487***	0.334***	0.262***	0.420***	0.227***
	(0.009)	(0.014)	(0.033)	(0.020)	(0.027)	(0.021)	(0.032)	(0.019)	(0.016)	(0.022)	(0.018)	(0.012)
HTD sq.	0.002***	0.002	0.003	0.005	-0.002	-0.003	0.004***	0.005**	0.002	-0.001	0.004*	0.000
	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
HTD	-0.040***	-0.019	0.004	-0.037	0.015	0.023	-0.141***	-0.068**	-0.034	-0.009	-0.025	-0.022
	(0.009)	(0.011)	(0.043)	(0.026)	(0.024)	(0.044)	(0.039)	(0.025)	(0.026)	(0.039)	(0.020)	(0.029)
Cold day	-0.021	-0.007	0.037	-0.007	-0.005	-0.016	-0.033	-0.024	-0.035	0.055	0.027	-0.065*
	(0.013)	(0.008)	(0.029)	(0.013)	(0.016)	(0.022)	(0.023)	(0.023)	(0.027)	(0.033)	(0.017)	(0.031)
precip_30_pri	0.000	0.000	-0.001	-0.001	0.000	-0.000	0.000	0.001	0.001	-0.003**	0.002*	0.002*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	0.146***	0.087***	0.133***	0.088***	0.169***	0.218***	0.147***	0.137***	0.165***	0.187***	0.464***	0.060**
	(0.011)	(0.014)	(0.032)	(0.022)	(0.037)	(0.028)	(0.025)	(0.027)	(0.023)	(0.045)	(0.022)	(0.020)
Secondary	0.217***	0.237***	0.094*	0.047	0.007	0.223***	0.390***	0.175***	0.204***	0.180	0.261***	0.202***
	(0.011)	(0.022)	(0.047)	(0.036)	(0.084)	(0.031)	(0.028)	(0.025)	(0.031)	(0.162)	(0.023)	(0.021)
Tertiary	0.450***	0.559***	0.383***	0.333***	0.181*	0.598***	0.696***	0.337***	0.511***	0.483**	0.491***	0.466***
	(0.015)	(0.024)	(0.049)	(0.039)	(0.084)	(0.041)	(0.057)	(0.039)	(0.038)	(0.159)	(0.028)	(0.038)
Married	-0.053***	0.140***	0.205***	0.039	0.176**	-0.311***	-0.123***	-0.086*	0.064*	0.242***	-0.076**	-0.025
	(0.013)	(0.020)	(0.057)	(0.029)	(0.061)	(0.037)	(0.034)	(0.039)	(0.032)	(0.064)	(0.025)	(0.027)
Separated	-0.483***	-0.474***	-0.254	-0.080	-0.833***	-0.681***	-0.503**	-0.451**	-0.298***	-0.875***	-0.502***	-0.390***
	(0.035)	(0.057)	(0.192)	(0.063)	(0.114)	(0.089)	(0.189)	(0.170)	(0.056)	(0.243)	(0.143)	(0.064)
Divorced	-0.581***	-0.397***	-0.289*	-0.346***	-0.439***	-0.548***	-0.241	-0.803***	-0.344***	-0.371***	-0.599***	-0.372***
	(0.029)	(0.035)	(0.134)	(0.044)	(0.113)	(0.116)	(0.137)	(0.112)	(0.072)	(0.098)	(0.073)	(0.058)
Widowed	-0.289***	-0.239***	-0.050	-0.151**	-0.012	-0.237***	-0.308***	-0.347***	0.056	0.168	-0.269***	-0.277***
	(0.025)	(0.036)	(0.082)	(0.048)	(0.101)	(0.069)	(0.062)	(0.076)	(0.068)	(0.110)	(0.058)	(0.052)
Domestic partnership	-0.200***	-0.085**	-0.274**	-0.124	-0.078	-0.357***	-0.747	-0.014	-0.168***	-0.095	0.330**	-0.209***
	(0.024)	(0.026)	(0.090)	(0.081)	(0.081)	(0.105)	(0.695)	(0.248)	(0.037)	(0.126)	(0.104)	(0.043)
children	0.155***	0.240***	0.121*	0.229***	0.029	0.113***	0.220***	0.147***	0.055*	0.046	0.153***	0.118***
	(0.012)	(0.018)	(0.050)	(0.026)	(0.062)	(0.031)	(0.031)	(0.028)	(0.026)	(0.060)	(0.023)	(0.027)
Age	-0.004***	-0.013***	-0.017***	-0.021***	0.005*	-0.001	-0.001	0.003**	-0.016***	0.002	-0.008***	-0.003***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
native	0.253***	0.306***	0.328***	0.056	0.072	0.267	0.025	0.004	0.366***	0.123	0.138**	0.048
	(0.024)	(0.032)	(0.054)	(0.047)	(0.048)	(0.215)	(0.110)	(0.132)	(0.080)	(0.074)	(0.043)	(0.060)
month_dev	0.020	0.043	-0.113	-0.021	0.011	0.175**	-0.104	0.089	0.109	-0.139	0.036	0.149
	(0.039)	(0.031)	(0.075)	(0.079)	(0.069)	(0.065)	(0.125)	(0.067)	(0.065)	(0.080)	(0.065)	(0.118)
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1436978	274345	58739	136776	19750	78891	115849	91218	180230	21092	217251	242837

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Effect of HTD on income, subjective health, and SWB in 5 years

	(1) Ln Income	(2) Health Problems (0/1)	(3) SWB in 5 years
HTD Day Interview	-0.32*	-0.006	-0.046
	(0.014)	(0.004)	(0.033)
HTD in 1-15 days before interview	-0.11	-0.004	-0.011
	(0.008)	(0.003)	(0.015)
HTD in 16-30 days before interview	0.002	-0.001	-0.041**
	(0.012)	(0.003)	(0.016)

Note: Predicted marginal effects based on OLS model with Subjective Well-being as dependent variable. Standard errors clustered at region-year level in parentheses. Controls include age, age^2, age^3, sex, marital status, education, children, native citizen, deviation from survey month from the usual in region.
* $p < 0.05$. ** $p < 0.01$

Table 7 Marginal effect of additional hot day by region and respondent characteristics

	(1) All	(2) Male	(3) Female	(4) <65 years	(5) >65 years	(6) Income > 40%	(7) Income <40%
Global	-0.036**	-0.039**	-0.034**	**-0.032**	**-0.064**	**-0.042**	**-0.023***
	(0.008)	(0.009)	(0.009)	**(0.009)**	**(0.013)**	**(0.009)**	**(0.011)**
E.U.	-0.014	-0.020	-0.007	-0.011	-0.021	-0.019*	-0.007
	(0.010)	(0.011)	(0.010)	(0.09)	(0.014)	(0.009)	(0.013)
Rest Europe	0.030	0.038	0.004	0.012	0.065	-0.003	0.065
	(0.044)	(0.040)	(0.033)	(0.036)	(0.054)	(0.033)	(0.045)
Commonwealth	-0.028	-0.027	-0.032	**-0.013**	**-0.135**	-0.024	-0.040
	(0.023)	(0.028)	(0.023)	**(0.023)**	**(0.040)**	(0.024)	(0.027)
Australia	0.014	-0.003	0.028	0.006	0.040	0.033	-0.017
	(0.020)	(0.025)	(0.023)	(0.020)	(0.027)	(0.021)	(0.034)
Southeast Asia	0.023	0.016	0.001	0.012	0.031	0.017	0.018
	(0.040)	(0.043)	(0.041)	(0.041)	(0.063)	(0.042)	(0.045)
South Asia	-0.132**	**-0.107**	**-0.155**	-0.131**	-0.085	-0.140**	-0.094*
	(0.038)	**(0.040)**	**(0.040)**	(0.039)	(0.056)	(0.039)	(0.046)
East Asia	-0.062**	-0.075**	-0.055*	-0.054*	-0.131*	-0.067**	-0.060*
	(0.023)	(0.027)	(0.025)	(0.025)	(0.042)	(0.024)	(0.030)
Latin America	-0.031	-0.025	-0.025	-0.027	0.001	-0.031	-0.024
	(0.024)	(0.022)	(0.021)	(0.021)	(0.030)	(0.023)	(0.025)
North America	-0.003	0.006	-0.012	0.015	-0.061	0.023	-0.029
	(0.039)	(0.045)	(0.045)	(0.042)	(0.051)	(0.040)	(0.047)
Mena	-0.029	**-0.037***	**-0.007**	-0.023	-0.017	-0.011	-0.022
	(0.018)	**(0.017)**	**(0.018)**	(0.016)	(0.039)	(0.017)	(0.019)
SubSaharan Africa	-0.027	-0.022	-0.024	-0.025	0.021	-0.021	-0.010
	(0.026)	(0.26)	(0.028)	(0.026)	(0.041)	(0.028)	(0.029)

Predicted marginal effects based on OLS model. Standard errors clustered at region-year level in parentheses. Bold numbers refer to statistically significant differences at 5% between pairwise predictions (male-female, older-younger, or poorer-richer). * $p < 0.05$. ** $p < 0.01$

Table 8: Effect by World Bank Income classification

	(1)	(2)	(3)	(4)	(3)	(4)
	Low income countries	**Lower middle income countries**	**Upper middle income countries**	**High income countries**	**Colder country**	**Hotter country**
Additional hot day	-.018	-.060**	-.051**	-.010	-.031*	-0.053**
	(0.029)	(0.019)	(0.017)	(0.09)	(0.012)	(0.013)

Hot country= if more than 15 days above 35 degree per year on average. Income classification based on World Bank definition.

Table 9: Income satisfaction measure

	(2)	(3)	(1)
	HTD -> Income	**Income -> SWB**	**Non-Income**
Global	0.008	-1.56	-0.028
EU	0.007	-0.804	-0.007
Rest Europe	0.013	-0.855	0.014
Commonwealth	0.011	-0.724	-0.017
Australia	0.002	-0.876	0.011
Southeast Asia	0.009	-0.609	0.021
South Asia	0.016	-0.581	-0.119
East Asia	0.014	-1.039	-0.052
Latin America	0.006	-0.691	-0.026
North America	0.000	-0.948	-0.019
Mena	-0.013	-0.776	-0.035
Sub Saharan Africa	0.008	-0.532	-0.023

Note: Same specification as in Table 3, but satisfaction with income measured on a scale from 1-4 is used instead of log income.

Figure 11: Predicted marginal effect of HTD by country
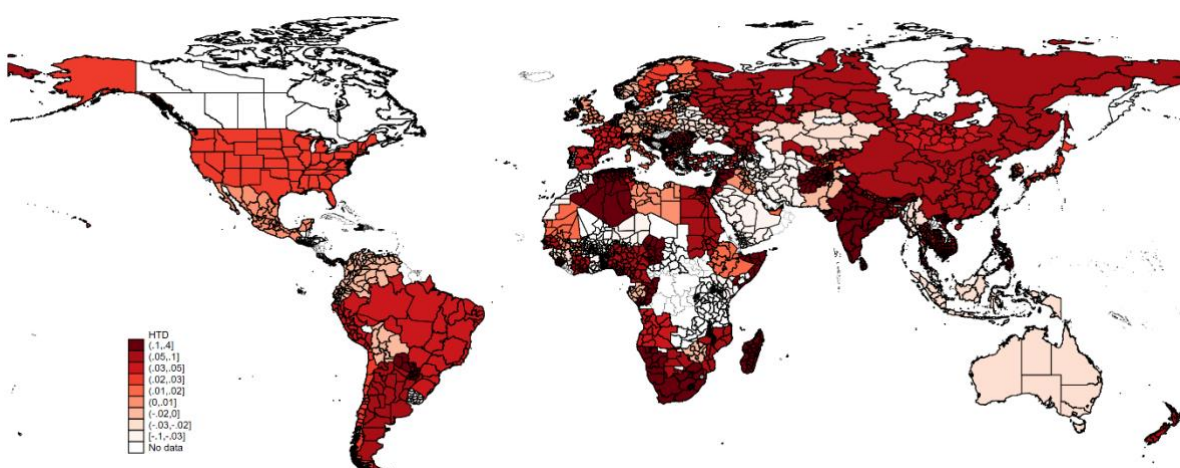
Note: Predicted marginal effects based on OLS model 3 of Table 2 with additional interaction term of country and HTD.
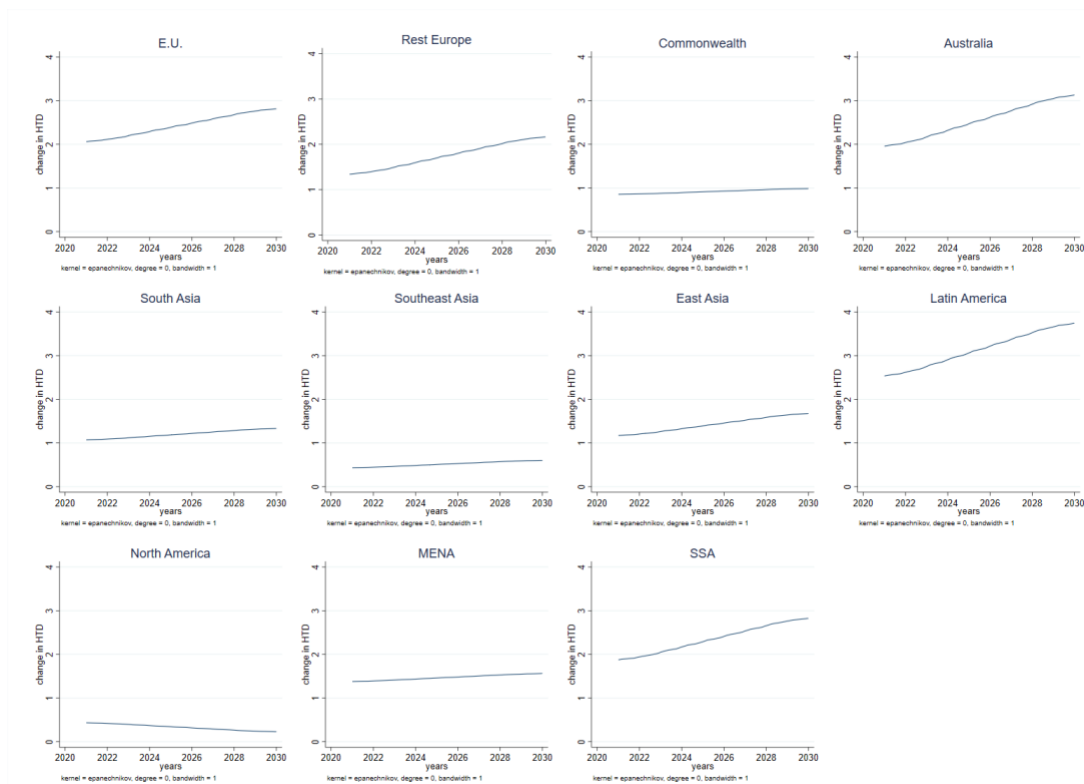
Figure 12: Projected change in SWB by world region due increasing HTD (benchmark 2019)
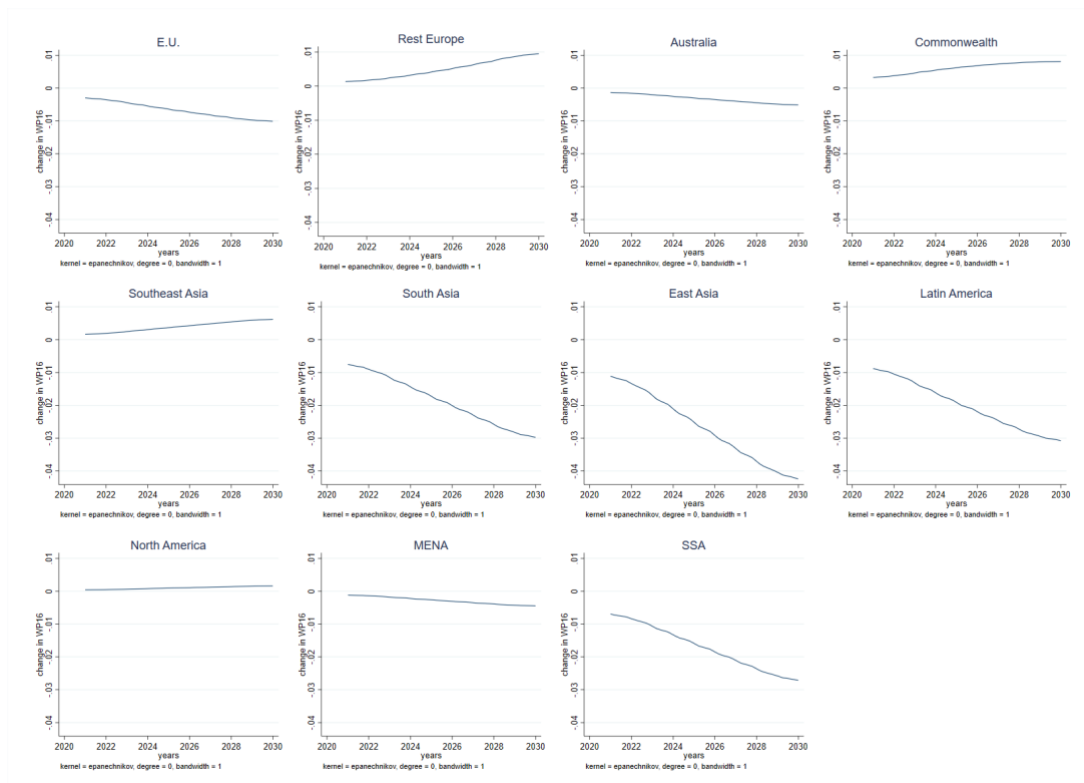
Note: Predictions based on projected changes in HTD and world region specific structural equation models as in Table 3.

Figure 13: Projected change in HTD (2021 – 2030)

Note: Projections based on linear model with region specific trends. Figures show local polynomial smoothing with rule of thumb bandwidth of 1.