Essays on the Economics of Climate Change

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ABSTRACT

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Climate change is a major environmental threat and likely one of the most important challenges of our time. In particular, climate extremes –such as heat waves– can have a significant negative effect on society. Yet, many impacts of climate change are poorly understood and binding international climate change agreements are notoriously hard to reach.

This work deals with the economics of climate change in three separate essays. The first one introduces a new methodology to estimate the impacts of climate extremes on public health. The second utilizes this methodology to assess the impacts of several climate change scenarios on Europe. The third explores a way to increase cooperation on climate change mitigation policies through explicit communication of the uncertainty of future climate change impacts.

In general, human mortality shows an oscillatory pattern on top of a nonlinear trend. It tends to be highest in winter and lowest in summer. The nonlinear trend follows changes in health policies, economic growth rates, and other institutional factors. The first essays shows that singular spectrum analysis can be used for the estimation of this base rate mortality and thus allows to isolate the impacts of climate extremes on human mortality. This methodology is an improvement over approaches based on fixed effects or classic spectral analysis. It makes it possible to extend climate impact analysis to regions and countries for which there are no detailed data from hospital records as only coarse monthly data on mortality are needed.

The danger of climate change lies not necessarily in the shift in average temperatures, but more so the increase in frequency of extreme heat events. Yet, while heat waves become more common, cold spells become less frequent. As both types of extreme

temperature events increase human morbidity and mortality, the net effect of this shift is unknown. The second essay finds that a scenario of moderate warming can have a positive net effect on some European countries, creating winners and losers. In contrast –severe warming as a result of failed climate change mitigation policies– affects all examined European countries in a negative way. There would be no winners, just losers.

As a result of the uncertainty associated with it, climate change poses a different challenge than other social dilemma situations: The negative effects of climate change do not necessarily take place incrementally. While this should be a focal point for policy makers, the costs of climate change tend to be presented within an expected utility framework. Yet, the potential behavioral reactions to this uncertainty are –so far– neither explored nor accounted for in game-theoretic models of climate coalition building. The third essay finds that cooperation in a public goods game can be increased when the uncertainty is communicated explicitly. This means that uncertainty should not be hidden behind expected costs and benefits, but rather be acknowledged when the goal is to form a climate change mitigation agreement.

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Dedication

Meinen Eltern. Danke für alles.

Introduction

Climate change is frequently featured in the media. Be it because of the yearly negotiations on international climate policy, because of a widespread draught, or because the past year has –yet again– been the hottest in the history of temperature records. The basic science behind climate change is taught in schools and universities, but we still have not agreed on how to coordinate our efforts against it and how to limit the potential damages.

Why is this the case? The underlying cause of climate change is well known — our emissions of greenhouse gases into the atmosphere leads the earth to heat up. These emissions need to be reduced and eventually completely halted. The issue that makes climate change such a tremendous challenge is that a unilateral reduction of greenhouse gases is likely to have negative net impacts on the respective country. As climate change mitigation policies must aim at internalizing the costs of greenhouse gas emissions, companies in the respective countries face higher costs and are thus at a comparative disadvantage. Benefits on the other hand are felt all around the world, making climate change one enormous prisoner's dilemma.

Besides the detrimental incentive structure when it comes to climate change mitigation, framing climate change as global warming further complicates things. While –on average– the temperature is indeed rising, this portrayal oversimplifies the problem. The change in temperature varies significantly across both geography and time. Climate change affects some countries more than others and there is be a high degree of variation in time. Further, even a minor shift in average temperature leads to a major shift in extreme temperature events. Figure I-1 illustrates this issue using maximum daily temperatures from Europe:

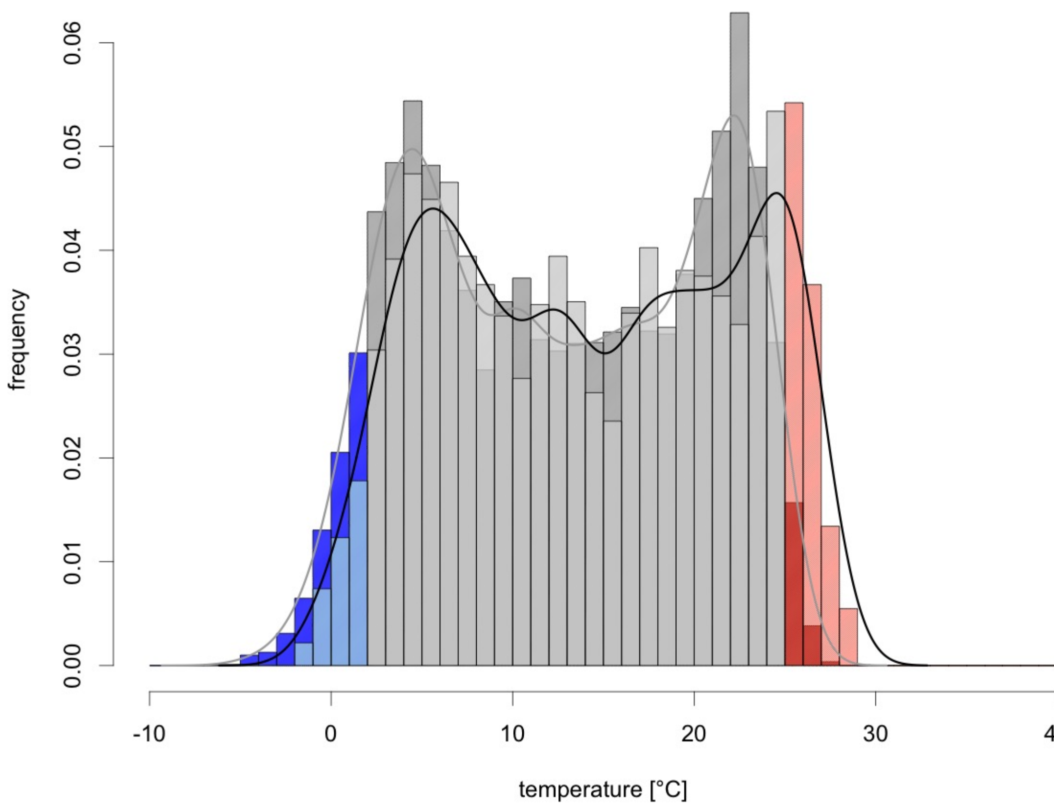

Figure I-1: **Shift in Temperature Distribution in Europe.** The dark probability mass function shows the distribution of maximum daily temperatures in Europe during 2001 to 2010, while the light probability mass function shows the distribution of the 1951 – 1980 reference climatology.

For the reference period from 1951 to 1980, the average daily maximum temperature in Europe was 12.73°C. In the last century, from 2001 to 2010, the average daily maximum temperature was 14.38°C, meaning that the temperature increase was only 1.65°C on average. Yet, by 2001 to 2010, the hottest events –defined as the hottest

1% of the reference period, had already multiplied in frequency by 8.6 times. As it is temperature extremes –not the average temperature– that cause most damage, the political focus should be shifted accordingly.

On top of this, the complex nature of the climate system adds further complications and can result in sudden, highly nonlinear changes. It is possible that there are several –currently unknown– thresholds for the atmospheric level of carbon dioxide and other greenhouse gases. Upon reaching these, there is the possibility of a sudden shift in climate-sensitive environmental systems that far exceed the rather slow and gradual change that is currently observed. There is a great deal of uncertainty about sudden shifts and the future impacts if climate change in general, making it very difficult to properly assess the optimal degree of climate change mitigation. To simplify decision-making for policy makers, the likelihood and damage of the various effects of different climate change scenarios are aggregated into a single number, expected costs. While this approach does make the comparison of different scenarios easier, it masks complexity and provides the illusion of certainty. As a result, it is also undermining the precautionary principle and supports the widespread belief in the possibility to adapt to climate change. This technocratic view –and ultimately "arrogant faith" (Gore, 2013, p. 240)– might lead to inaction and subsequently to higher damages due to climate change.

This work deals with several of the above-mentioned aspects of the economics of climate change. The first essay introduces a new methodology to estimate the effects of extreme temperature events. The second essay deals with the future impacts of temperature extremes as well as with the associated uncertainty under different climate change scenarios. The third essay explores a way to make international climate cooperation more likely through communicating said uncertainty.

Climate change is one of the biggest challenges of our time: Countries need to cooperate now and reduce global greenhouse gas emissions in order to be able to prevent most damage. Creating a stable and effective international climate policy regime is not an easy task, but a necessary one. Many small additional pieces of knowledge are needed to come closer to such an agreement; this work might provide one or two of them.

Chapter 1

Climate Change Impact Estimation Using Singular Spectrum Analysis

Heat waves are a threat to society in many ways and are becoming increasingly frequent. Hence estimating their impact is key when it comes to the design of effective climate change adaptation measures.

Here I present and explore a new methodology –based singular spectrum analysis– to do so. Using data from 27 European countries, I derive excess estimates for mortality in three different temporal resolutions. Excess estimates are then regressed against a heat wave measure in order to assess the impacts of extreme heat.

The results show that singular spectrum analysis has analytical advantages over an approach using fixed effects or standard spectral analysis. Monthly-level mortality rates are sufficient to gain meaningful estimates for the impact on heat waves on mortality.

This finding demonstrates that singular spectrum analysis can be a powerful tool to understand the impacts of climate change. It complements existing methodologies when it comes to low-resolution data that show characteristic yearly fluctuations such as mortality rates.

1.1 Motivation

Climate change is a considerable environmental threat (Watts et al., 2015), affecting society in several different ways. Among these, heat waves possibly pose the highest risk to public health (IPCC, 2014b). Episodes of high temperatures increase both human morbidity (Semenza, McCullough, Flanders, McGeehin, and Lumpkin, 1999) and mortality (Semenza et al., 1996), particularly among the elderly and those with pre-existing medical conditions (Kovats and Hajat, 2008). They further have an averse effect on crop yields (Schlenker and Roberts, 2006, 2009) and might negatively impact the economy.

As a result of climate change, events of extreme heat have become more frequent in recent years (Hansen, Sato, and Ruedy, 2012). A further increase in frequency is projected for the future (Fischer and Knutti, 2015). This means that high-impact events will become more common and will no longer be an exception.

The impact of heat waves on human mortality has been studied extensively using case studies. Some authors focus on particular cities (see e.g. Marmor, 1975; Changnon, Kunkel, and Reinke, 1996; F. Ballester, Corella, Pérez-Hoyos, Sáez, and Hervàs, 1997; Whitman et al., 1997; Vandentorren et al., 2004; Anderson and Bell, 2009; Madrigano, Ito, Johnson, Kinney, and Matte, 2015), while others examine slightly broader geographic areas (see e.g. Huynen, Martens, Schram, Weijenberg, and Kunst, 2001; Fouillet et al., 2006; Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2016). Common to both is the use of micro-level health data, usually taken from daily hospital records. While this approach allows to look at the causes of death, it is only feasible if the needed detailed data are available. It is because of this limitation that a different approach is needed: This work tries to do so. It estimates the effects of extreme heat events without relying on health data from hospitals. As a result, the geographic scope of the analysis can be extended. Countries, for which data from hospitals do not exist or are costly to acquire, can be included, as can minor heat waves. This helps gaining a more conclusive picture of the effect of heat waves on human mortality.

1.2 Methodology

This work examines the impact of heat waves on Europe in a two-step process. First, base rate mortality is derived by applying a method of time series decomposition on country-level mortality rates. Second, the excess estimates are regressed against a heat wave measure in order to quantify the effects of extreme heats events.
Heat waves tend to be limited to a few days at a time. They occur at irregular intervals and not usually every year at the same time. It is because of this, that excess mortality due to heat waves is not correlated with base rate mortality. The effect of heat waves is superimposed on the other factors affected mortality. As a result, it is possible to differentiate the effects of heat waves from the other causes of human mortality.

Mortality Rates and Excess Mortality

In general, mortality rates show a seasonal fluctuation. The number of deaths is highest in winter and lowest in summer. Although periodic, these fluctuations are not necessarily harmonic and can be subject to modulations in amplitude. On top of this, mortality rates show a distinct pattern for each country: They are affected by many factors such as level of economic development, availability of medical services, societal norms, and prevalence of endogenous diseases. Combined, these factors influence and change base rate mortality slowly in a nonlinear fashion. As a result, the base rate mortality can be subject to change over time. If, by way of example, a country experiences a shift in unemployment rates, its mortality rates can be expected to change as well (Stuckler, Basu, Suhrcke, Coutts, and McKee, 2009). This, together with other factors such as changes in national health care expenditures (Kennelly, O'Shea, and Garvey, 2003), leads to a nonlinear trend in base rate mortality that is not related to variations in extreme temperature events or in other environmental factors.

When causes of mortality are analyzed, different types of health data on different temporal scales are utilized.

Cause-specific mortality data provide information on the underlying and contributing causes of death. Further information about the deceased such as day of death or personal details can be included as well, depending on the source of the data. With this data, there can be a privacy concern if causes of death can be attributed to individuals, such as when obtained from a hospital. This is not the case if the cause-of-death statistics are accumulated by type.

All-cause mortality data do not differentiate between the individual causes of death. Given the lack of privacy concerns in case of low geographic resolution, this type of data is usually most readily available. Different national and international statistical offices such as the National Center for Health Statistics or Eurostat provide all-cause mortality data for large geographic areas.

In this work, all cause mortality data are used. Data that includes the cause of death are not publicly obtainable for a significant part of the intended study area. Further, given distinct national policies, data received from different countries would need to be standardized first in order to be comparable. This introduces an additional level of uncertainty. Finally –and most importantly– for large areas of the world, no reliable cause-of-death statistics exist. Even when a country reports these data, it might not be reliable (Burger et al., 2012). Changes in the reporting of the underlying cause of death can introduce biases (Helweg-Larsen, 2011). As a consequence, there is a need for analysis methods that use all-cause mortality data of low resolution until sufficiently reliable cause-of-death data are available universally. The methodology used in this work is thus not intended to replace established approaches, but rather to complement them and to extend the analysis.

Impacts of Heat Waves on Public Health

Climate change has both direct and indirect effects, interacting with socio-economic factors, forming health risks for society (Watts et al., 2015). In general, mortality rates have a U-shaped relation with temperature; both extreme cold and extreme heat are increasing mortality rates (F. Ballester et al., 1997). The effects of climate change include increased thermal stress, increased risk of flood, and increased prevalence of certain infectious diseases (McMichael, Woodruff, and Hales, 2006). Heat waves –due to their short-lived nature– affect public health primarily directly. The longer and more intense a heat wave, the more severe its impact (Anderson and Bell, 2011).

Generally speaking, episodes of high temperatures can lead to overheating of the body. Several related conditions can be differentiated (see Bouchama and Knochel, 2002): Mere discomfort, as a result of a fairly small elevation in body temperature (Epstein and Moran, 2006), is referred to as heat stress. Heat exhaustion is a state characterized by dehydration and electrolyte loss as well as, possibly but not necessarily, slightly elevated temperature. Left untreated, heat exhaustion can progress to heat stroke (Luber and McGeehin, 2008), which is a critical condition with significantly increased body temperature. Heat stroke severely affects the nervous system and can possibly lead to coma and death (Luber and McGeehin, 2008). Accordingly, during episodes of high temperatures, hospitals see an increased influx of patients due to dehydration, heat exhaustion, as well as heat stroke (Semenza et al., 1999), some of which die (Fouillet et al., 2006).

There is evidence that vulnerability towards heat waves differs across individuals and communities. Women and the elderly are most affected (e.g. Fouillet et al., 2006; Robine et al., 2008), as the body's thermoregulative capability –especially in women after the menopause– declines with age (Hajat, Kovats, and Lachowycz, 2007). There are also pre-natal impacts. Episodes of high temperatures during the second and third trimester of a pregnancy can have a negative impact on birth weight (Deschenes, Greenstone, and Guryan, 2009), though the exact mechanism of action is currently still unknown.

Further, people with pre-existing conditions experience more severe effects (e.g. Semenza et al., 1996, 1999), mainly as a result of the heat compounding the effects of the pre-existing conditions (Keatinge and Donaldson, 2004). One of the conditions in question are cardiovascular diseases (F. Ballester et al., 1997; Huynen et al., 2001; Patz, Campbell-Lendrum, Holloway, and Foley, 2005; Fouillet et al., 2006; Madrigano et al., 2015), that are prevalent in large parts of society and a leading cause of death by themselves (Mensah and Brown, 2007. Heat waves can exacerbate the medical problems associated with these conditions. When facing heat stress, a body usually speeds up blood circulation as part of the thermoregulative response. The ability to do so is impaired in those with cardiovascular conditions (Bouchama and Knochel, 2002) and in the elderly in general (Gronlund, Zanobetti, Wellenius, Schwartz, and O'Neill, 2016). This increases the probability of more severe effects such as heat stroke and –ultimately– increases the likelihood of death. A similar coupling exists between heat stroke and diseases of the respiratory system as well as of the nervous system. Heat strokes tend to affect both systems (Bouchama and Knochel, 2002), thus aggravating existing conditions. As a result, people affected by diseases of the respiratory systems face a higher likelihood of heat wave-related death (F. Ballester et al., 1997; Huynen et al., 2001; Patz et al., 2005; Fouillet et al., 2006; Hajat et al., 2007) as well as those affected by diseases of the nervous system (Fouillet et al., 2006). Further notable is the case of those with degenerative diseases such as dementia. Here, medication provided against the condition in question inhibits the body's ability to thermoregulate (Zanobetti, O'Neill, Gronlund, and Schwartz, 2013), again resulting in a situation where heat waves have a higher likelihood of severe outcomes. Other medication and drugs can have similar effects and possibly lead to increased vulnerability during a heat wave (Luber and McGeehin, 2008).

A common denominator of all the factors concerning human physiology is that there is no lasting effect of heat. Once an episode of high temperatures is over and once one's body temperature has cooled down sufficiently, no lasting effect is to be expected. This claim finds empirical support in the literature (Anderson and Bell, 2009). Hence, heat wave-related excess mortality comes in form of a sharp peak, which is superimposed on the base rate mortality (Kovats and Hajat, 2008). It is this characteristic, that ultimately allows the detection of heat-wave related mortality using singular spectrum analysis. As is subsequently shown, this allows the separation of signal from noise.

Given that the primary victims of heat waves are those with a lowered life expectancy, there is an argument in favor of mortality rates being reduced directly after a heat wave. This is referred to as harvesting effect. Literature is somewhat divided on the topic. Some authors do not find any evidence for the harvesting effect (e.g. Robine et al., 2008) or are inconclusive (e.g. Huynen et al., 2001), while others find evidence (e.g. Baccini et al., 2008). A review article on the effects of heat waves on mortality notes that the harvesting effect is only mentioned in few studies (Åström, Forsberg, and Rocklöv, 2011). Nevertheless, the theoretic argument in favor of the harvesting effect remains. Given that there are many confounding factors –and hence a lot of noise– when it comes to causes of human mortality, the signal of the harvesting effect might just be too weak in order to be detectable in many studies. In a similar fashion, there is also an argument that heat waves that occur early in any given year are more impactful than those occurring later. The reason for this could either be the harvesting effect –as the more susceptible individuals are killed in the first heat wave– or adaptation, as individuals who have not yet experienced heat waves might be less prepared than those that have (Barnett, Hajat, Gasparrini, and Rocklöv, 2012).

This also illustrates that vulnerability to heat waves is not only based on human physiology, but also on socio-economic factors. As Changnon et al. (1996) and Madrigano et al. (2015) show for the case of Chicago and New York City respectively, black individuals are more likely to die during a heat wave than non-black individuals. This disparity between the races can be partially explained by differences in access to air conditioning (O'Neill, Zanobetti, and Schwartz, 2005) as well as by differences in general health (Gronlund et al., 2016). Hence, the disparity could thus be corrected with appropriate public health policies. Similarly, a lack of education and poverty in general increase vulnerability to extreme heat (Reid et al., 2009; O'Neill, Zanobetti, and Schwartz, 2003). Some communities simply lack the capability to prepare for heat waves. This insight is consistent with literature on resilience research and human geography (see e.g. Adger, 1999). These vulnerabilities multiply when adverse socio-economic conditions and fragile health concur (Gronlund, Berrocal, White-Newsome, Conlon, and O'Neill, 2015).

Preparing for and adapting to heat waves can take several forms. First, there is behavioral change, which can be promoted by institutions of public health. Weisskopf et al. (2002) find that –using data from Milwaukee– that, when controlling for confounding factors, the expected number of deaths due to any given heat wave decreased between 1995 and 1999. They suggest that improvements in public health institutions, particularly public heat advisories that inform the public about upcoming heat waves, are a possible explanation for this phenomena. Other authors (Semenza et al., 1996;

Easterling et al., 2000; Luber and McGeehin, 2008) also emphasize the importance of optimizing warning systems and increasing awareness when it comes to reducing deaths due to natural hazards. Second, there is physical adaptation such as via the introduction of private air conditioning. Barreca et al. (2016) show that the impact of a single heat wave on human mortality in the US has been decreasing over the twentieth century and that this can be explained by the widespread adoption of air conditioning. A similar development can also be expected in Europe, where market penetration of air conditioning has increased over the last two decades (Pezzutto, Fazeli, De Felice, and Sparber, 2016). Air conditioning seems particularly important in an urban setting, where –due to the urban heat island effect (McGeehin and Mirabelli, 2001)– nighttime temperatures are higher than in a rural environment (Changnon et al., 1996). The positive effect of air conditioning is independent of socio-economic factors (Ostro, Rauch, Green, Malig, and Basu, 2010) and it is even possible to use air conditioning to compensate for physiological risk factors as Barnett (2007) shows for the case of cardiovascular diseases.

Adaptation can also be observed in a broader sense – communities and cities in the US and Europe that are located in a warmer climate are less sensible to episodes of high temperatures than those located in a colder climate (Vandentorren et al., 2004; Baccini et al., 2008; Deschenes and Greenstone, 2011; Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2015). This intuitively makes sense as it is reasonable to expect populations to be adapted to their local climate (Kovats and Hajat, 2008). Yet, this also means that estimates of the impact of heat waves for one population cannot readily be used for another one (Anderson and Bell, 2009).

Heat Wave Measure and Data

In the literature there is no consensus on a universal definition of heat waves (Robinson, 2001). Definitions are generally chosen based on the goal of the respective study as well as on the background of the involved researchers (T. T. Smith, Zaitchik, and Gohlke, 2013).

In its simplest form, a heat wave can be defined as an event during which the minimum or maximum daily temperature reaches a pre-defined threshold. This threshold can either be fixed to be universal (see e.g. Robinson, 2001) or it can be defined relative to a local climatology (see e.g. Gronlund et al., 2016). A more complicated form demands that both minimum and maximum temperatures are above their respective thresholds (see e.g. Robinson, 2001) or asks for an interpolation of the daily maximum and minimum temperatures (Snyder, 1985). Further, some definitions include duration next to intensity and look for a minimum length of the event such as two (Madrigano et al., 2015), three (Meehl and Tebaldi, 2004) or even five days (Huynen et al., 2001).

Besides temperature, humidity is an important determinant for heat stress. Consequently, heat waves measure can be constructed using a combination thereof. Epstein and Moran (2006) suggest using the discomfort index, which is based on both dry-bulb and wet-bulb temperature, as it is straightforward to calculate and easy to use. More complicated measures such as the apparent temperature exist and are used in research (see e.g. Gronlund et al., 2015).

Some authors find that different measures for heat waves do not influence their results by a lot (Gronlund et al., 2016). Here, explorative data analysis confirmed this sentiment. The likely reason for this finding being the coarse temporal resolution of the data used. Accordingly, a comparatively simple measure for heat waves was chosen. It is based on daily maximum temperatures alone and utilizes thresholds that are defined relative to the local climatology.

The climate data set used, E-OBS 12.0, is provided by the European Climate Assessment & Dataset project (Haylock et al., 2008) and contains the maximum daily temperatures for Europe from 1950 to 2015 on 0.25 degree grid cells. For each of these grid cells, a reference summer climatology is calculated, using the months of April to September during the period of 1951 to 1980. Based on each grid cell's reference climatology, a heat wave is defined as an event exceeding the $+2\sigma$-threshold. The heat wave measure is the number of days per month that meet this criteria.

Given that it is not plausible to assume that the population within a country is uniformly distributed, the individual grid cells are weighted by population. The importance of this weighting becomes apparent when thinking about the spatial heterogeneity within Europe. Mountainous regions tend to support a lower population density while being subject to fewer heat waves than lower lying areas. Assuming a uniform distribution of population in mountainous countries such as Spain or Austria will thus underestimate the actual heat stress on the population. It is therefore important to consider the actual geographic distribution of the population. The data on population density, GEOSTAT 2011 V2, are provided by Eurostat and the European Forum for GeoStatistics (Eurostat and EFGS, 2015) on 1 km^2 grid-cells. Unfortunately, only information on the distribution of the European population in 2011 is available. Nevertheless, this is more appropriate than to just assume a uniform distribution of the population within the respective countries.

In order to assess the temporal resolution needed for meaningful results, the monthly data are also accumulated to quarters and years.

Estimating Excess Mortality

In order to identify the impact of extreme heat events, excess mortality estimates need to be isolated. Singular systems analysis has many advantageous properties that are useful when doing so. Its fundamental idea is to capture as much of the underlying structure of the data with as few functions as possible. Effectively, it is a specialized application of principal components analysis on a single time series. Up to a certain degree, it is similar to classic spectral analysis as it decomposes a time series into a set of orthogonal functions. Yet, unlike classic spectral analysis, these orthogonal functions need not be a set of harmonics. As a result, singular spectrum analysis is more robust and agnostic with respect to the underlying structure of the data. This is useful when isolating excess mortality: First, modulations in amplitude can be accounted for (Elsner and Tsonis, 1996) as can non-sinusoidal, i.e. anharmonic, motions (Ghil et al., 2002). This allows to account for exogenous factors –such as an unusually mild winter– that might have short-term effects on mortality. Then, nonlinear filtering (Elsner and Tsonis, 1996) allows to capture the nonlinear trend in the base rates. Thus, a wide range of country-specific long-term shifts such as resulting from changes in the political landscape can be accounted for without facing the challenge of an omitted variable bias. Last, singular systems analysis is a non-parametric method. Hence no particular structure needs to be imposed on the data, even if the respective data series are short and noisy (Vautard, Yiou, and Ghil, 1992; Ghil et al., 2002).

Other country-level estimations methods, fixed effects models and spectral analysis, need to enforce one of two conditions. These conditions can be relaxed here as a result of the non-parametric nature of singular systems analysis. Fixed effects models (see e.g. Deschenes et al., 2009; Deschenes and Greenstone, 2011) generally need to assume linear additivity, unless the time series spans over a long time horizon (Bai, 2009), which is not the case here. Classic spectral analysis (see e.g. Granger and Hatanka,

1964) on the other hand relies on representing data using a combination of sine and cosine functions. Using singular systems analysis means to be able to relax both of these conditions. As a result, this allows to widen the set of examined countries to those that have only recently started to collect data on public health.

Fixed effects models are common in econometric research, where they are used to capture unobserved heterogenous effects of explanatory variables (Montgomery, 2009), including effects of time (see e.g. Currie and Neidell, 2005). The underlying idea is to introduce treatment-specific intercepts into a standard regression model while keeping the effect of the independent variables on the dependent variable the same across the treatments. In this work, there are two treatments for each country-specific time series: Month fixed effects and year fixed effects, The effect of heat waves on the dependent variable, β_c is assumed as time-invariant within a country. This model can be conceptualized as follows:

$$x_{c_t} = \alpha_{c_{my}} + h_{c_t}\beta_c + \epsilon_{c_{my}} \tag{1.1}$$

Here, x_{c_t} is the dependent variable of country c at time t, h_{c_t} is the independent variable, that is the heat wave measure, and $\alpha_{c_{my}}$ is the estimated month- and year-specific intercept. β_c is the estimated interaction coefficient and $\epsilon_{c_{my}}$ is the month- and year-specific error coefficient.

The standard spectral analysis approach uses a combination of sine and cosine functions to account for the seasonal variation in the time series. After subtracting the year-specific mean from the data, the Fourier transform of the resulting residual can be calculated. Assuming a perfect seasonal cycle, an ideal filter is applied and all other frequencies are set to zero. The filtered Fourier transform of the residuals is then transformed back into the time-domain. The result is the fitted estimate of the yearly fluctuation of the original time series.

Estimating excess mortality using singular spectrum analysis is done in several steps. First, lagged and de-meaned segments of the country-specific mortality rates are embedded into a vector space. Then, information in form of pairs of eigenvectors and eigenvalues are extracted from this vector space using spectral decomposition. The eigenvalues allow to select those eigenvectors that capture at least 5% of the total data variation; the other eigenvectors are discarded. Finally, the respective signal components can be reconstructed using the remaining eigenvectors. The sum of these reconstructed signal components represent the de-meaned base rate mortality.

The window length or embedding dimension, M_c, is chosen depending on the available data and the objective of the analysis. As the smallest resolvable frequency is inversely proportional to the embedding dimension, M_c needs to be long enough to resolve the seasonal oscillation. To increase separability, M_c should be a multiple of the length of this seasonal oscillation (Hassani, 2007). Further, M_c should not be longer than one third of the length of the original data series in order to avoid making statistical errors too influential (Vautard et al., 1992). In this work, 48 months is chosen as the window length for the analysis of the monthly mortality data of all 27 examined countries, meaning that the smallest resolvable frequency was $f = \frac{1}{48}\text{month}^{-1}$.

Using this window length, a trajectory matrix $\tilde{X}_c$, a M_c x N_c' multivariate data set, is created for each country c using lagged and de-meaned segments of the original mortality data series X_c of length N_c:

$$\tilde{X}_c = \begin{bmatrix} (x_{c_1} - \bar{x}_c) & (x_{c_2} - \bar{x}_c) & \dots & (x_{c_{N_c'}} - \bar{x}_c) \\ (x_{c_2} - \bar{x}_c) & (x_{c_3} - \bar{x}_c) & \dots & (x_{c_{N_c'+1}} - \bar{x}_c) \\ \vdots & \vdots & \vdots & \vdots \\ (x_{c_{M_c}} - \bar{x}_c) & \dots & \dots & (x_{c_{N_c}} - \bar{x}_c) \end{bmatrix} = \begin{bmatrix} \tilde{x}_{c_1} & \tilde{x}_{c_2} & \dots & \tilde{x}_{c_{N_c'}} \\ \tilde{x}_{c_2} & \tilde{x}_{c_3} & \dots & \tilde{x}_{c_{N_c'+1}} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{c_{M_c}} & \dots & \dots & \tilde{x}_{c_{N_c}} \end{bmatrix} \tag{1.2}$$

The number of columns of this trajectory matrix is M_c and the number of columns of is $N'_c = N_c - M_c + 1$.

Using singular value decomposition, the trajectory matrix can be deconstructed into its left singular vector, W_c, into its right singular vector, S_c, and into a diagonal matrix of its singular values, V_c (Elsner and Tsonis, 1996):

$$\tilde{X}_c = W_c S_c V_c^T \tag{1.3}$$

The principal components, P_c, and their eigenvectors, E_c, can be directly obtained from this decomposition:

$$P_c = S_c V_c^T \tag{1.4}$$

$$E_c = W_c \tag{1.5}$$

Using both principal components and eigenvectors, the set of signal components R_{κ_c} can then be reconstructed for each country c, following the approach by Ghil et al. (2002):

$$R_{\kappa_{c_t}} = M_{c_t} \cdot \sum_{\kappa \in \varkappa_c} \sum_{j=L_{c_t}}^{U_{c_t}} P^{\kappa}_{c_{t-j+1}} E^{\kappa}_{c_j} \tag{1.6}$$

$\varkappa_c$ is the set of modes used in the decomposition. As a result of the use of lagged segments of the original data, the reconstruction of the endpoints of the signal components only includes some of the principal component and eigenvector pairs. The respective lower summation bounds, L_{c_t}, and upper summation bounds, U_{c_t}, are defined as follows (Ghil et al., 2002):

$$(M_{c_t}, L_{c_t}, U_{c_t}) = (\frac{1}{t}, 1, t) \qquad \text{for } 1 \le t \le M_c - 1 \tag{1.7}$$

$$(M_{c_t}, L_{c_t}, U_{c_t}) = (\frac{1}{M_c}, 1, M_c) \qquad \text{for } M_c \le t \le N_c - M_c + 1 \tag{1.8}$$

$$(M_{c_t}, L_{c_t}, U_{c_t}) = (\frac{1}{N_c - t + 1}, t - N_c + M_c, M_c) \qquad \text{for } N_c - M_c + 2 \le t \le N_c \tag{1.9}$$

M_{c_t} is the normalization factor needed to adjust the scale of the reconstructed signal components for the difference in number of included principal component an eigenvector pairs.

To determine how many of the reconstructed modes are actually of importance, the signal-to-noise ratio –that is the fraction of the total variance, that is explained by each reconstructed signal component– is calculated:

$$\mathrm{SNR}_c = \frac{I \cdot D_c}{tr(D_c)} \tag{1.10}$$

Here, I is the identity matrix and D_c is the diagonal matrix of the eigenvalues with:

$$D_c = \frac{S_c S_c^T}{N_c - 1} \tag{1.11}$$

As part of this analysis, all signal components with a signal-to-noise ratio of less than 5% are discarded, as are signal components that represent oscillations with a frequency higher than $f = \frac{1}{12}\text{month}^{-1}$. The remaining k_c signal components plus the mean mortality rates together form the base rate mortality — subtracting it from the actual mortality rates leads to the excess mortality estimates, y_c.

In this work, between two and five signal components are retained and reconstructed per country. On average, these signal components capture 64.48% of total variation in mortality. Table 1.1 below shows the number of retained signal components and the level of captured variance for each of the 27 examined countries.

country	number of retained signal components	% of total variance captured
Austria	3	84.21
Belgium	2	67.57
Bulgaria	3	67.50
Croatia	3	64.52
Czech Republic	3	52.60
Denmark	3	68.46
Estonia	3	67.90
Finland	3	40.90
France	3	58.82
Germany	3	58.87
Greece	4	65.84
Hungary	3	50.22
Italy	2	56.57
Latvia	3	59.76
Lithuania	4	77.34
Macedonia	3	64.48
Netherlands	3	52.28
Norway	3	62.65
Poland	3	54.38
Portugal	3	68.13
Romania	2	68.05
Slovakia	4	48.78
Slovenia	2	43.61
Spain	5	75.02
Sweden	3	57.18
Switzerland	3	67.70
United Kingdom	3	71.91

Table 1.1: **Retained signal components for mortality rates by country.** Number of the retained signal components for mortality rates by country and their share of total variance of mortality.

Figure 1.1 shows the reconstructed signal components for the monthly mortality data from Germany together with their power spectrum. The first two reconstructed signal components show a peak in their power at $f = \frac{1}{12}\text{month}^{-1}$, indicating that both represent the seasonal component of the base rate mortality. The third reconstructed signal components shows a peak in its power at $f = \frac{1}{48}\text{month}^{-1}$. Here, this frequency is the smallest resolvable frequency, meaning that this signal component depicts a nonlinear trend in the base rate mortality.

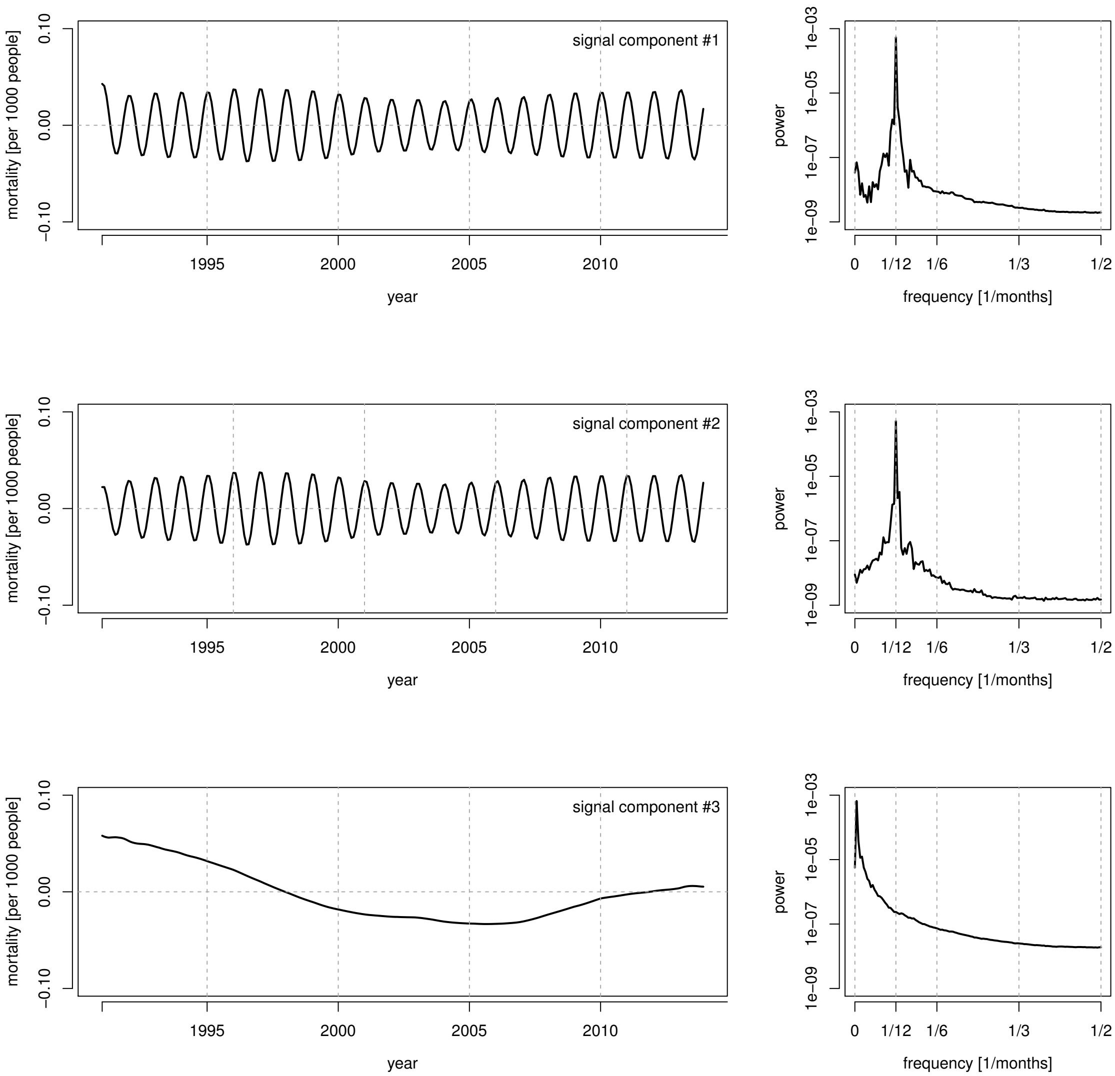

Figure 1.1: **Signal components and their power spectrum for German mortality rates.** The first two signal components represent a seasonal fluctuation; the third signal component represents a nonlinear trend.

When combining these three signal components with the mean mortality rate, base rate mortality is obtained. Figure 1.2 shows this base rate mortality plotted on top of the observed mortality for Germany. It captures a total of 58.87% of the variation in the observed mortality rates.

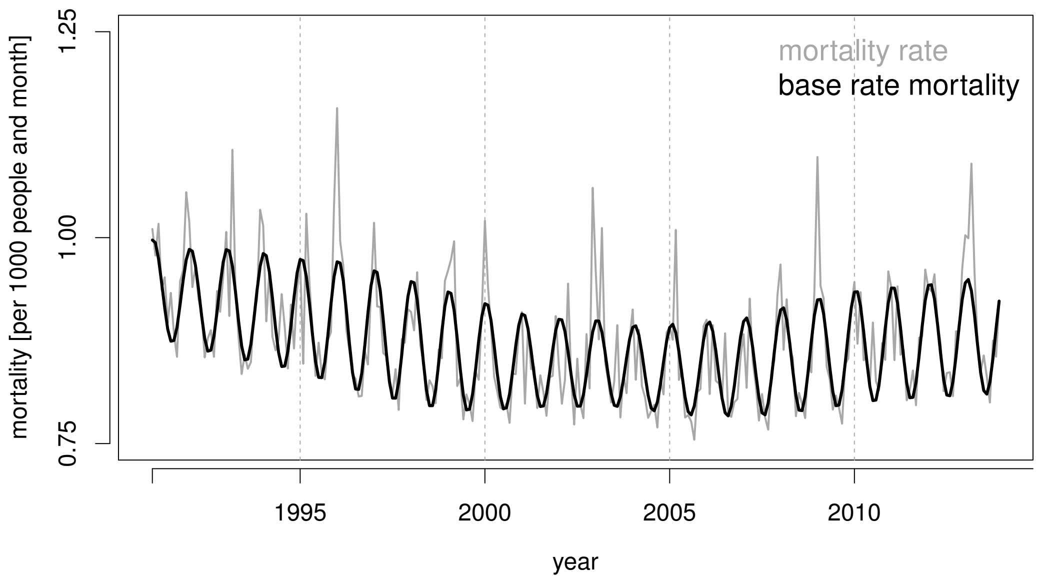

Figure 1.2: **Base rate mortality estimates and observed mortality rates in Germany from 1990 to 2013.** Base rate mortality estimates are plotted in black; observed mortality rates are plotted in grey.

Subtracting the reconstructed signal components and the mean from the observed mortality rates leads to the estimates of excess mortality. As excess mortality should be influenced by heat waves, high levels in the heat wave measure should coincide with peaks in excess mortality. Figure 1.3 shows that this is the case, again using the example for Germany.

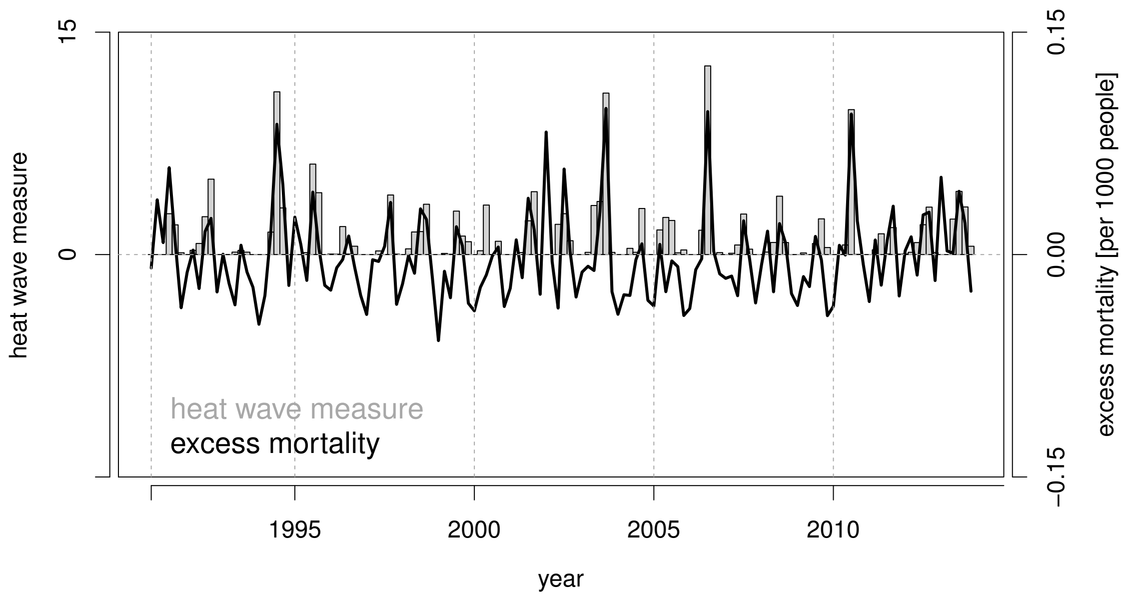

Figure 1.3: **Excess mortality estimates and heat wave measure in Germany during April to September, 1990 to 2013.** Excess mortality estimates are plotted in black; heat waves measure is plotted as grey bars.

Finally, excess mortality estimates y_c are regressed in an ordinary least squares approach against the heat wave measure:

$$y_{c_t} = \theta_c + h_{c_t}\eta_c + \xi_c \tag{1.12}$$

Here, h_{c_t} is the heat wave measure of country c at time t, θ_c is the intercept, η_c is the estimated interaction coefficient, and ξ_c is the error-coefficient.

1.3 Results

Results are divided into three parts: First, the estimated effect of heat waves on human mortality –using the monthly-level data– is provide for each country. Second, comparisons of the performance of the presented methodology with the established literature using monthly-level data are made. Third, comparisons between the different temporal scales are drawn.

Heat Waves and Their Effect on Human Mortality

Estimates for the impact of individual heat waves on the respective countries are given in table 1.2 together with their level of significance. Further, for each country, an estimated number of deaths including standard errors is provided.

country	data length (years)	interaction coefficient (deaths per heatwave and 1000 people)		number of deaths caused by heat waves (average per year)		average mortality caused by heat waves (percent of total mortality)
Austria	54	0.011	***	311	(± 34)	0.40
Belgium	39	0.008	***	423	(± 53)	0.40
Bulgaria	20	0.015	***	463	(± 94)	0.45
Croatia	22	0.011	***	294	(± 36)	0.60
Czech Republic	19	0.007	***	353	(± 63)	0.34
Denmark	54	0.012	***	150	(± 20)	0.28
Estonia	25	0.010	***	40	(± 10)	0.24
Finland	54	0.015	***	101	(± 14)	0.22
France	19	0.011	***	5410	(± 499)	1.03
Germany	23	0.010	***	5609	(± 481)	0.67
Greece	54	0.066	***	661	(± 47)	0.68
Hungary	20	0.010	***	464	(± 84)	0.37
Italy	54	0.029	***	3302	(± 259)	0.59
Latvia	18	0.014	***	84	(± 19)	0.28
Lithuania	20	0.013	***	127	(± 29)	0.32
Macedonia	19	0.008	***	65	(± 14)	0.37
Netherlands	24	0.008	***	1045	(± 87)	0.78
Norway	54	0.008	***	104	(± 18)	0.26
Poland	19	0.009	***	1229	(± 209)	0.34
Portugal	54	0.027	***	1059	(± 81)	1.14
Romania	19	0.007	***	566	(± 201)	0.24
Slovakia	18	0.007	***	201	(± 41)	0.39
Slovenia	18	0.005	***	72	(± 19)	0.40
Spain	39	0.039	***	3563	(± 271)	1.07
Sweden	54	0.012	***	239	(± 28)	0.28
Switzerland	54	0.007	***	153	(± 19)	0.26
United Kingdom	32	0.005	***	2012	(± 427)	0.35

*** p<0.01, ** p<0.05, * p<0.1

Table 1.2: **Interaction coefficients of heat wave measures.** Interaction coefficients represent the increase in monthly mortality rates for each heat wave event; heat-caused excess deaths are given as yearly average per country.

The estimates vary significantly across countries. Some countries such as Spain and Greece suffer from higher mortality during individual high temperature events than other countries such as Germany or Switzerland. One reason for this is that the examined countries differ significantly with respect to the age structure of their population, their health care system, as well as their economic and institutional capabilities.

When looking at the average number of deaths, two types of countries are least affected in terms of total deaths: Countries in Scandinavia and countries with a small population. Based on the estimates, the total number of deaths due to heat waves can be calculated — on average, around 28,100 people die every year in the 27 countries combined. This considerable number stresses the importance of avoiding heat wave-related deaths when it comes to successful public health policies. It can be derived that an average of 0.61% of all mortality in the examined 27 countries is excess mortality caused by heat waves. This estimate goes up to 1.14% in the worst-affected country, Portugal.

Relative Model Performance

The performance of the approach using singular spectrum analysis as compared to that of the fixed effects model and classic spectral analysis is evaluated using leave-one-out cross validation. In case of the approaches using singular spectrum analysis and spectral analysis, the estimates of excess mortality are regressed against the heat wave measure, in case of the fixed effects model, the mortality rate is regressed against the heat wave measure using year and month fixed effects. One observation is dropped from the sample and then predicted using the remaining observations. This is repeated for each observation. The difference between predicted values and actual observation is used to evaluate absolute performance below in table 1.3:

country	leave-one-out cross validation using root mean squared error (singular spectrum analysis)	(fixed effects model)	(spectral analysis)
Austria	0.03	0.03	0.41
Belgium	0.03	0.03	0.43
Bulgaria	0.06	0.04	0.71
Croatia	0.03	0.03	0.39
Czech Republic	0.02	0.02	0.27
Denmark	0.03	0.03	0.35
Estonia	0.04	0.04	0.53
Finland	0.03	0.03	0.33
France	0.03	0.03	0.32
Germany	0.02	0.02	0.30
Greece	0.05	0.04	0.55
Hungary	0.03	0.03	0.47
Italy	0.04	0.03	0.44
Latvia	0.04	0.04	0.56
Lithuania	0.04	0.04	0.58
Macedonia	0.03	0.03	0.49
Netherlands	0.02	0.02	0.26
Norway	0.03	0.02	0.30
Poland	0.02	0.02	0.30
Portugal	0.04	0.04	0.52
Romania	0.05	0.03	0.62
Slovakia	0.03	0.02	0.32
Slovenia	0.03	0.03	0.39
Spain	0.03	0.02	0.35
Sweden	0.02	0.02	0.30
Switzerland	0.02	0.02	0.31
United Kingdom	0.03	0.03	0.45

Table 1.3: **Performance comparison of three different identification strategies using leave-one-out cross validation.** The approach using singular systems analysis is the described in depth in the main body of this chapter; the fixed effects model uses year- and month-fixed effects; spectral analysis uses an optimal band filter.

Using root mean squared error as a measure of performance, this shows that classic spectral analysis performs significantly worse than both of the other approaches. Consequently, it is not discussed here any further. As the actual number of deaths caused by heat waves is unknown, leave-one-out cross validation is unsuitable to classify the performance of either methodology relative to a more conventional approach.

Model Performance Comparison

The 2003 heat wave in Europe, that affected larger parts of Western Europe, offers a good opportunity for comparing the model performance. This heat wave took place during the first half August 2013 and primarily affected France. The heat wave was unprecedented in terms of intensity and duration (Vandentorren et al., 2004; Poumadère, Mays, Le Mer, and Blong, 2005) and had a severe impact on many European countries. A consequence of this was a certain lack of preparedness. In Paris, where the highest spike in mortality was recorded (Fouillet et al., 2006), many of the victims lived alone, without access to air conditioning (Poumadère et al., 2005). Socio-economic factors aggravated the underlying physiological conditions and mortality was generally higher in cities that had experience less heat before (Vandentorren et al., 2004). The combination of extreme temperatures with these issues resulted in a very high death count. Subsequently, the heat wave was extensively discussed in the media and widely picked up for the academic study of the relationship between heat waves and human mortality.

One study on the 2003 heat wave (Robine et al., 2008) seems particularly suited for the comparison of performance. Most of the other research on the 2003 heat wave focuses on individual countries such as France (Fouillet et al., 2006), Italy (Conti et al., 2005), and Switzerland (Grize, Huss, Thommer, Schindler, and Braun-Fahrländer, 2005). Some research concentrates on even smaller samples such as individual cities (Vandentorren et al., 2004) or vulnerable individuals (Vandentorren et al., 2006). As the underlying mortality data are not consistent across these research papers, the creation of a single data set of estimates of excess deaths is not straightforward at all. There would be a need for harmonizing estimates. Hence, a comparison using such a data set would always have to deal with confounding errors. Differences in estimates could be due to shortcomings in the model or due to imperfect harmonization. Hence the comparison with Robine et al. (2008). They derive heat-related excess deaths from daily data for a period of four months during summer 2003, using the same period during the years of 1998 to 2002 as a baseline. While this analysis does not take cause-of-death into account, it provides estimates for 16 European countries, which is significantly more than any other research study. Table 1.4 compares predictions from the approach using singular spectrum analysis and from a fixed effects model with the results from Robine et al. (2008).

month	excess deaths during summer 2003		
	(singular spectrum analysis)	(fixed effects model)	(Robine et al., 2008)
June	12,305	9,125	12,387
July	10,254	7,410	10,456
August	37,831	27,822	42,545
September	914	838	4,816
total	61,304	45,195	70,188

Table 1.4: **Comparison of estimated excess mortality with the established literature.** The approach using singular systems analysis is the described in depth in the main body of this chapter; the fixed effects model uses year- and month-fixed effects; Robine et al. (2008) use hospital-level data.

As can be seen in the table, the fixed effects model consistently underestimates the number of heat-related excess deaths. In contrast, the model used in this work provides estimates for June and July 2003 that are very close to the results by Robine et al. (2008). Its estimates for August and September 2003, however, are smaller. The reason for this can not be determined conclusively. Given the available temperature data, Robine et al. (2008) should not find as many excess deaths in September as they did. This enigma illustrates the problem with models based on all-cause mortality data; noise can not always be identified without fail.

One possible explanation for the different performance across the models is that both the fixed effects model and classic spectral analysis need to assume a certain structure of the data, such as linear additivity of the underlying factors. This limits both to representing harmonic oscillations, while singular spectrum analysis is not limited in the same way. As can be seen in figure 1.1, the seasonal component of the base rate mortality is subject to modulations of its amplitude, while the trend component follows a nonlinear motion. The combination of these effects might be beyond the limits for both fixed effects model and classic spectral analysis.

Temporal Scales

Depending on the specific region, monthly country-level mortality rates might not be available. Hence it seems important to test whether the presented methodology also works with even coarser data. For that purpose, the data on mortality were accumulated on a quarter- as well as on a year-level before estimating excess mortality using singular spectrum analysis. As table 1.5 shows, this does not lead to significant estimators in most cases.

In only three –in case of the quarter-level data– or four –in case of the yearly data– out of the 27 countries, estimates for the impact of heat waves can be derived that are significant at the $p = 0.05$ level. This suggests that data on the monthly-level are needed in order to make meaningful inferences about the impact of heat waves on human mortality.

country	regression coefficient					
	(month-level)		(quarter-level)		(year-level)	
Austria	0.009	***	0.001		0.005	
Belgium	0.006	***	0.000		0.001	
Bulgaria	0.012	***	0.003		0.001	
Croatia	0.009	***	0.002		0.002	
Czech Republic	0.006	**	0.002		0.005	**
Denmark	0.010	***	0.000		-0.003	
Estonia	0.009	***	0.000		-0.001	
Finland	0.014	***	-0.003		-0.003	
France	0.009	***	0.003	**	0.005	
Germany	0.008	***	0.001		0.004	
Greece	0.060	***	0.009	*	0.049	***
Hungary	0.009	**	0.001		0.003	
Italy	0.026	***	0.009	***	0.000	**
Latvia	0.011	**	0.004		0.003	
Lithuania	0.011	***	0.002		0.014	
Macedonia	0.006	***	0.005	***	0.019	***
Netherlands	0.006	***	-0.001		-0.003	
Norway	0.008	***	-0.001		-0.004	
Poland	0.008	***	0.000		-0.002	
Portugal	0.024	***	0.003		0.004	
Romania	0.005	*	0.000		0.002	
Slovakia	0.006	***	0.001		0.002	
Slovenia	0.004	**	0.002	*	0.001	
Spain	0.032	***	0.004		0.020	*
Sweden	0.011	***	-0.002		-0.009	
Switzerland	0.006	***	0.001		0.006	
United Kingdom	0.005	**	0.000		0.003	

*** p<0.01, ** p<0.05, * p<0.1

Table 1.5: **Comparison of regression coefficients of different temporal scales.** For each country and temporal scale, regression coefficients are provided with level of significance.

Note that the estimates in the table above are derived using all available data, including the winters, in order to preserve comparability. As a result, the estimates based on the monthly-level data are slightly different than the ones presented before.

1.4 Discussion

As demonstrated, the methodology presented provides worthwhile insights into the large-scale effects of heat waves on human mortality. It does not need detailed daily health data, which can be difficult and costly to acquire. Monthly mortality rates on a country level are sufficient to obtain reasonable estimates. As a result, the analysis of the impact of heat waves can be expanded to countries for which no detailed data are available.

Robustness and Limitations

As the comparison with the results from Robine et al. (2008) shows, heat-related excess deaths can be estimated using singular spectrum analysis in a meaningful way. The comparison also shows that the estimated numbers are likely underestimating the number of deaths due to extreme heat waves. In case of the heat wave in 2003, the difference across the four observed months was 12.66%. Overall, due the rarity of events of this magnitude, the absolute difference is likely smaller.

A significant part of the underestimation is the result of delayed mortality. A considerable number of heat-related excess deaths occurred in September 2003, that is during a period which was not characterized by extraordinary heat. This provides evidence for extreme heat waves possibly having a lasting effect on public health. However, the introduction of lags into the regression model did not improve its performance, suggesting that this might only matter for the most extreme heat waves. As these kind of heat waves can be expected to become more frequent as a result of ongoing climate change, this corollary should be kept in mind when predicting the future impact of climate change on public health.

All of the 27 examined countries had continuous time series of health data of at least

18 years. Time series longer than that do not increase the model performance — the root mean squared prediction error in leave-one-out cross validation does not decrease with increased length of the time series. This means that this particular application of singular spectrum analysis shows similar robustness with respect to short time series as is expected from the general application (see Vautard et al., 1992).

Yet, in some cases, no meaningful estimates can be derived even in case of the monthly data. This is the case for countries where only extremely short continuous time series of public health data exist. This is the case for Albania, where there are only three years of continuous mortality data available. There is a similar challenge in case of small population numbers such as for Liechtenstein with a population averaging about 30,000 people at a time. In either case, the signal is not strong enough to be separated from the noise. These limitations can not overcome by any approach using data on a country level. For either of these cases, detailed data from hospitals are needed.

Conclusions

While episodes of high temperatures seem –at least as of now– not to be the major driver of human mortality in the examined European countries, they are bound to become more important. Consequently, public health and climate adaptation policies need to address extreme heat. This work estimates that heat waves cause a share of up to 1.18% of all mortality in countries across Europe – the issue is therefore not to be underestimated. In a changing climate, with increasingly frequent temperature extremes, it does not seem unlikely to expect a rise in heat-related excess mortality in the near future. Some of the heat wave-related deaths might be avoidable through adaptation (see e.g. Barreca et al., 2016); further research on the large-scale effects of heat waves on human mortality in Europe is thus needed.

The presented methodology, based on singular spectrum analysis, is not without limitations, particularly when it comes to very short time series and very low numbers of affected individuals. Yet, it outperforms the more standard approaches using fixed effects or combinations of sine- and cosine-functions to model the yearly fluctuations in base rate mortality. Generally speaking, it captures a higher share of variability in mortality as it does not force a particular structure on the data. As the results indicate, singular spectrum analysis is a valid tool to estimate the large-scale effects of heat waves on human mortality and offers certain analytical advantages over the more established approaches.

While micro-level approaches using detailed hospital-level data could provide more insights into particular events, the needed data are not available for many countries, making comparisons across broader regions essentially impossible. Thus, macro-level approaches like the one presented, are a valuable complement to the existing literature and can help to draw the attention of policy makers to the dangers of extreme temperature events as well as to the adaptation measures needed.

Chapter 2

The Effects of Extreme Temperature Events in Europe: Winners and Losers of Climate Change

The increasing frequency of heat waves is the most perceivable effect of climate change and accordingly is most frequently discussed in the media. While this increase is framed as a threat to public health, the accompanying decrease in cold spells also offers tremendous advantages. The resulting net effect for different climate scenarios is mostly unknown.

Here I exploit the periodic fluctuations in mortality rates using a combination of frequency and time domain time series analyses in order to identify the magnitude of both trends.

I find that climate change does not need to be a threat to public health in Europe, depending on the degree of warming: Under a scenario of moderate climate change with fewer cold spells, excess mortality can be reduced by as much as 1.0%. Yet, under a scenario of severe climate change with significantly more frequent heat waves, a net increase in mortality –on average 3.6%– is expected.

Taken together, this demonstrates the need for effective climate change mitigation; otherwise there will only be losers, no winners.

2.1 Motivation

The impact of extreme temperature events is easily conceivable: Blistering heat causes discomfort, as does bitter cold. Either can lead to death. At a community level, linking these events to negative health outcomes is easily possible using data from hospitals. Yet, at many locations, this kind of data is noisy or not available at all, making a large-scale analysis difficult or impossible. Accordingly, our understanding of the interplay between temperature extremes and public health is predominantly limited to case studies, mostly cities or particular events. Only recently, comprehensive studies of a larger geographic area, the United States, have been published (Barreca, 2012; Barreca et al., 2016). However, given the structural and socio-economic differences across countries –resulting in possibly very different trajectories with respect to vulnerability to extreme temperature events– even the latter study does not support strong conclusions about other parts of the world. There is evidence that the impacts of extreme temperature events vary across communities (Baccini et al., 2008), possibly due to acclimatization (Anderson and Bell, 2009) or due to access to adaptation measures (O'Neill et al., 2005). This suggests that the change in the frequency of extreme temperature events due to climate change could have varying effects on different parts of the world.

Improving upon current understanding of the impact of extreme temperature events is crucial. Climate change can be perceived as a significant environmental threat to public health for many reasons (Watts et al., 2015); one of them being the upwards shift in the frequency of extreme temperature events (Easterling et al., 2000; Alexander et al., 2006) that occurs in addition to the increase of average temperatures. Heat waves are becoming more frequent and more intense (Meehl and Tebaldi, 2004), while cold spells are becoming less common. Both types of extreme temperature event have detrimental effects on human health (Barnett, 2007; Anderson and Bell, 2009). Either increases human morbidity and mortality (Díaz et al., 2005; J. Ballester, Rodo, Robine, and Herrman, 2016). Affected are primarily people with medical conditions and the elderly (Huynen et al., 2001; Analitis et al., 2008). Heat waves are likely more dangerous than cold spells (Barnett et al., 2012). Projections point towards a further increase in their occurrence (Fischer and Knutti, 2015) along with the shift in the current climatology as a result of ongoing anthropogenic climate change. As a result, catastrophes such as the August 2003 heat wave in Western Europe that caused ten thousands of deaths (Robine et al., 2008) might be a more common occurrence in the future. Hansen et al. (2012) –focusing primarily on hot extremes– describe this new climatology as "loaded climate dice" (p. 2418), framing it as a danger to public welfare in line with other literature (IPCC, 2014b). Yet, when considering the reduction of cold spells, moderate climate change might also be considered an opportunity –not a threat– when looking at public health.

This work tries to assess this question for the case of Europe. This location was chosen for several reasons. Europe consists of many small countries with different levels of economic development, each with their own economic and political system. Further, there are several climate zones in Europe, some of which are expected to shift as a result of climate change (Seneviratne, Lüthi, Litschi, and Schär, 2006). The resulting change in extreme heat and extreme cold events shows a significant degree of spatial heterogeneity (Elguindi, Rauscher, and Giorgi, 2013). Last, comparable data are available for most European countries, thanks to the work of the European Union and its statistical office. Together, this means that there are reliable data with a unique level of variation in both mortality and climate, making the identification of the effect of temperature extremes on public health comparatively easier in Europe than in many other parts of the world.

Mortality rates oscillate in a nonlinear motion, making classic time-domain approaches based on linearly additive fixed effects potentially misleading. This work uses a non-parametric method mirroring principal components analysis of a time series in order to avoid forcing a certain structure on the data. This method, singular systems analysis, can exploit both month-to-month and year-to-year variation and is used here to extract excess mortality from Eurostat's monthly mortality data on Europe. The method is described in detail in chapter 1 of this work.

Excess mortality is combined with an extreme temperature measure. This measure is based on the distribution of maximum temperatures relative to a baseline climatology using high resolution gridded climate data. Weighting the individual grid cells by population density allows to account for differences in the geographic features within the respective countries.

I begin by showing that extreme temperature events had a considerable impact on human mortality in Europe during the second half of the 20th century. Combined, heat waves and cold spells account for up to 1.78% of all mortality within a country. While there is a large degree of spatial heterogeneity, my analysis suggests that an average of 36,100 deaths per year are caused by temperature extremes in the examined 27 European countries.

Next, I demonstrate that climate change has already changed the pattern of heat waves and cold spells and that this has led to a net increase of excess deaths; over 17,000 additional people died in the last decade when compared to a 1951 – 1980 reference climatology. Increases in heat waves amounted to 25,600 deaths, while decreases in cold spells led to 8,600 fewer deaths. Individual countries suffered up to 1.14% of additional mortality. This result concurs with the viewpoint that climate change is a threat, yet it in itself does not allow predictions about the impact of a further changing climate.

Lastly, I analyze this impact of future climate change under two different scenarios, one of moderate and one of severe warming. While excess mortality could be reduced by up to 1.0% in case of moderate warming, on average it will increase by as much as 3.7% under severe warming. As a result of a combination of biophysical and socio-economic factors some regions will be affected more by climate change than others. Particularly countries bordering the Mediterranean Sea suffer from a drastic increase of heat waves early on while not profiting much from a decrease in cold spells. This approach allows to outline a roadmap of needed mitigation measures; countries that are affected negatively under both scenarios need to implement adaptation policies earlier than those only affected negatively by severe warming.

My findings suggest that climate change might further develop as threat to public health in Europe, but that it does not have to. In contrast, restricting it to a moderate level of warming offers benefits to several countries, primarily to France, as well as some of the Benelux countries and those in Scandinavia; thus creating winners and losers in the process.

2.2 Methodology

The methodology is based on the idea developed in the first chapter and extending upon the approach presented by Hansen et al. (2012). Excess mortality for 31 European countries is estimated using singular spectrum analysis on data from Eurostat (Eurostat, 2015). Data on maximum daily temperatures for Europe from 1950 to 2015 are again taken from European Climate Assessment & Dataset project (E-OBS 12.0, Haylock et al., 2008). This temperature data set is split into a summer- and a winter-half. Two reference climatologies –one for winter, one for summer– are calculated for each grid-cell using data from 1951 to 1980 only. The plus two- and plus three sigma-events of the reference climatology for summer are then defined as extreme heat event. Extreme cold events are defined correspondingly as the minus two- and minus three sigma-events of the reference climatology for winter. This is done for each grid-cell. Subsequently, these measures are used to define cold spells and heat waves for the entire data-set ranging from 1950 to 2014, summed up to the national level after being weighted by population-density (GEOSTAT 2011 V2, Eurostat and EFGS, 2015), and accumulated per month. Excess mortality is then regressed against the extreme temperature measure.

The future impact of climate change is assessed using forecasts on a 0.25 degree grid cell for the last decade of this century under two scenarios from 21 different climate models. The forecast data are taken from the NEX-GDDP climate scenarios, which are provided by the NASA Center for Climate Simulation (Thrasher et al., 2012). The predicted extreme temperature measures are averaged across the models to gain a best estimate for each scenario. To take account for demographic changes, the estimates for current excess deaths are regressed against age- and sex-specific mortality rates using data from Eurostat (2015). The estimates for the future impact of extreme temperatures are then modified accordingly using demography forecasts from the UN World Population Prospects (United Nations, Department of Economics, 2015).

2.3 Results

Extreme Temperature Events and Health

There is a great degree of variability in extreme temperature events and the associated excess mortality across and within the countries of Europe. Generally, the countries in Europe's South –such as Spain, Italy, and Greece– are affected greatly by frequent exposure to heat waves. In contrast, the Scandinavian countries

–in particular Norway and Sweden– face a higher degree of excess mortality due to cold spells. This heterogeneity is compounded by the varying impact of extreme temperature events as shown in table A-2 in the appendix. Some countries such as Spain and Greece experience a higher spike in mortality during a heat wave than other countries such as Germany and Switzerland. The same holds true for cold spell-related mortality. Countries such as Estonia are more vulnerable than other countries such as Norway. The reasons for this are based in the differences in the underlying socio-economic factors of the respective countries.

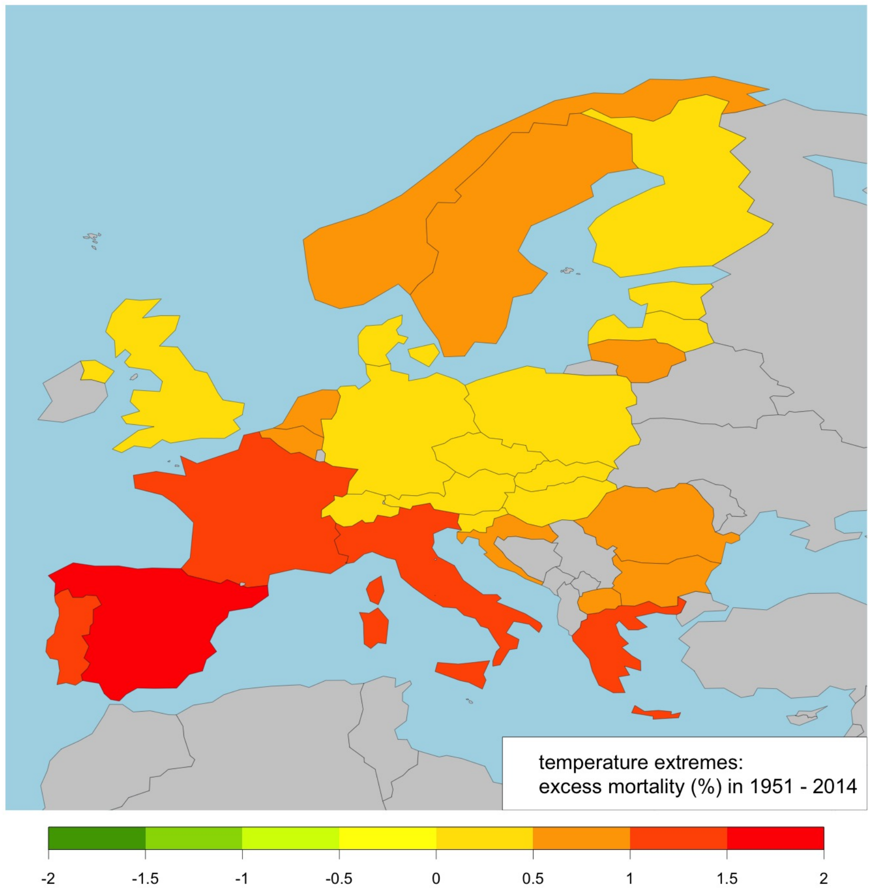

Figure 2.1: **Total share of excess mortality caused by temperature extremes in Europe between 1951 and 2014.** Excess mortality is expressed in % of the national mortality rates.

Combing the effect of heat waves and cold spells, as is done in figure 2.1, leads to the result that up to 1.78% –in case of Spain– of all mortality is excess mortality caused by extreme temperature events. This means that an average of 0.80% of all mortality and thus a total of over 36,100 deaths per year in the examined European countries during the period of 1951 to 2014 are due to heat waves and cold spells. To put this into context – the number of deaths due to traffic accidents is at a comparable level (Eurostat, 2015).

The Current Temperature Distribution

In more recent decades, the impact of temperature extremes has increased as the climate has already changed significantly. Events that are as cold as the coldest 1% temperature events of the 1951 – 1980 reference climatology were about eleven times less likely to occur during the last decade from 2001 to 2010. In contrast, events that are as hot as the hottest 1% temperature events of the 1951 – 1980 baseline climatology were about nine times as frequent during the same period. Figure I-1 in the introduction illustrates this shift in the temperature distribution.

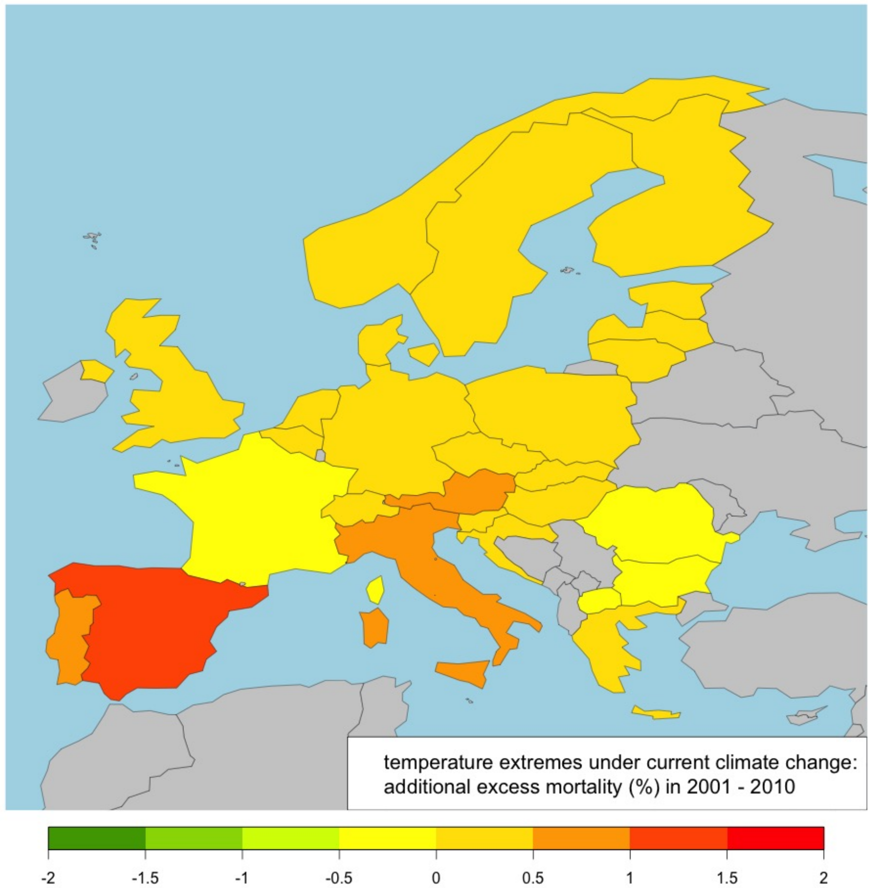

Figure 2.2: **Additional degree of extreme temperature-caused excess mortality in Europe during the decade of 2001 – 2010.** Additional degree of excess mortality is compared to the 1951 – 1980 baseline climatology and expressed in % of the national mortality rates.

The most significantly affected countries of this shift are those in Southern Europe, in particular Spain and Italy: They are subject to additional excess mortality of up to 1.14% of their total mortality. These countries were already affected severely by heat waves in the past; the reduction in cold spells is not of sufficient magnitude to compensate for the increase in temperature. In contrast, some countries profit from the shift. France and parts of the Balkans have not yet seen a drastic increase in heat waves, though they have profited from a decreased occurrence of cold spells, leading to a net-reduction in mortality. For most other European states –as figure 2.2 shows– current levels of climate change have not had a noticeable impact on net excess mortality. However, the overall impact of this shift is negative with an increase of 0.35% of mortality. The yearly total number of excess deaths due to heat events increased by around 25,600, while the yearly total number of excess deaths due to cold spells decreased by about 8,600. This means that climate change already claims over 17,000 lives per year in Europe.

Impacts of a Changing Climate

A further changing climate can affect this picture though. There is a high degree of uncertainty associated with respect to the level of global warming in the future (IPCC, 2014a). The Intergovernmental Panel on Climate Change, which is an authoritative body on climate change research, uses several different climate models to explore the extent of climate change under different scenarios. In its fifth and latest assessment report, 21 models and four scenarios, representative concentration pathways or RCPs, were used. Each of the RCPs assumes a different pathway for greenhouse gas concentrations in the atmosphere.

In this work, two of these scenarios –RCP 4.5 and RCP 8.5– are analyzed using all 21 climate models. The basis of RCP 4.5 is that emissions are stabilized and that the level of additional radiative forcing relative to pre-industrial levels is limited to 4.5 Wm^2 as well as not increasing beyond 2100. This can be considered a scenario of moderate warming in which climate policy is successfully mitigating most effects of global warming. In contrast, RCP 8.5 is a pessimistic scenario of severe warming, assuming that climate politics is failing and that the concentration of greenhouse gases in the atmosphere will rise beyond 2100, causing additional radiative forcing of over 8.5 Wm^2. Further underlying assumptions for this scenario include rapid population growth as well as very limited gains in terms of efficiency. Hence, this scenario assumes a drastically rising energy demand, which is increasingly satisfied with coal (Riahi et al., 2011). It is fair to say that this scenario is somewhat unlikely. Even though RCP 8.5 was not originally developed as a boundary condition for climate change (van Vuuren et al., 2011), the estimates of climate change impact –that are derived using it– can be treated as extreme upper bound estimates.

Currently, anthropogenic greenhouse gas emissions have led to an increase of radiative forcing of about 2.0 Wm^2 (IPCC, 2014a); it is not unreasonable to assume that the actual rise in temperature will fall somewhere between the two scenarios. Figure 2.3 and figure 2.4 explore both scenarios and show the estimated future level of excess mortality due to additional temperature extremes under each. Results can also be found in table A-3.

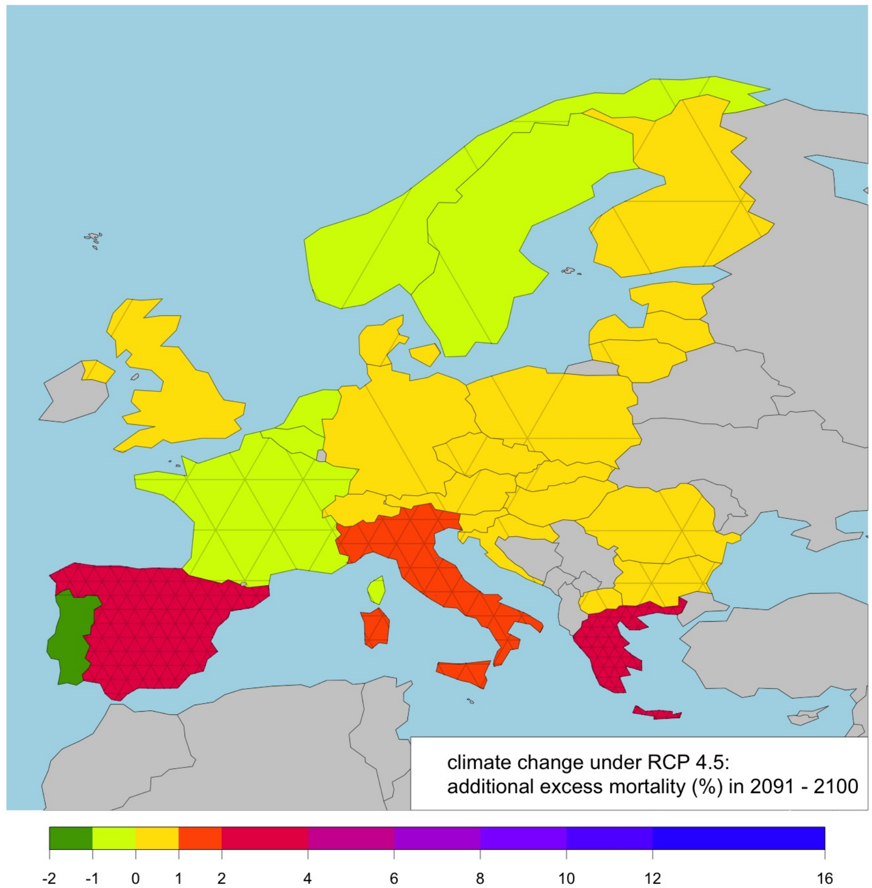

Figure 2.3: **Estimated future climate change-caused excess mortality in Europe in 2091 – 2100.** Additional excess mortality is expressed in % of the forecasted national mortality rates. It is calculated for the decade of 2091 – 2100 as compared to the 1951 – 1980 baseline climatology assuming a moderate change in climate under RCP 4.5. The triangles express uncertainty across the forecasts – the smaller the triangles, the higher the uncertainty.

Assuming moderate warming, as is depicted in figure 2.3, some European countries can be considered beneficiaries with a decrease in mortality of up to 1.0%. Parts of Northern and Western Europe, particularly France, the Benelux states Belgium and Netherlands, as well as the Scandinavian countries Norway and Sweden, will profit from a further reduction of cold spells. In contrast, countries in Southern Europe –mainly Spain, Greece, and Italy– will experience a considerable net-increase in mortality up to 3.7% due to more frequent heat waves. The average increase in mortality across all 27 countries is 0.5%. This result suggests that there will be winners and losers in case of moderate climate change – in order to avoid starkly diverging pathways of excess mortality, the beneficiaries should help the negatively affected countries with the needed adaptation measures.

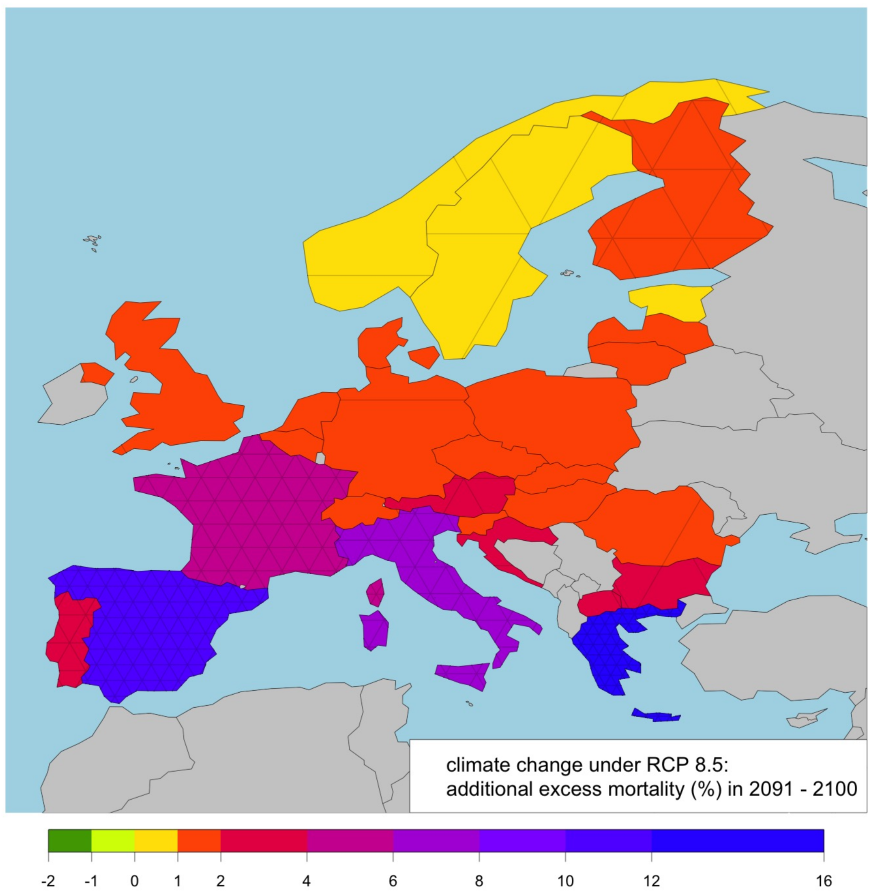

Figure 2.4: **Estimated future climate change-caused excess mortality in Europe in 2091 – 2100.** Additional excess mortality is expressed in % of the forecasted national mortality rates. It is calculated for the decade of 2091 – 2100 as compared to the 1951 – 1980 baseline climatology assuming a strong change in climate under RCP 8.5. The triangles express uncertainty across the forecasts – the smaller the triangles, the higher the uncertainty.

Assuming severe climate change, as shown in figure 2.4, there will not be any winners. Countries such as France, that could profit from a stark reduction of cold spells concurrent with only a slight increase in heat waves under a scenario of moderate warming, will not able to profit more from a continuing reduction of extreme cold events; they will be subject to a greater increase in heat waves. In particular Mediterranean Europe –as a subtropical region– will be affected severely with a high number of additional excess deaths. Overall, the average mortality increase is 3.6% under severe warming with a range from 0.6% to 15.9%.

2.4 Discussion

The projected increase in excess deaths is considerable, yet it is not the result of the shift in temperature alone. On the contrary, this particular development is a combination of climate change and of the European population aging. Projections (United Nations, Department of Economics, 2015) indicate that the share of people aged 50 years or older is increasing in all of the countries that are examined in this work; almost all of the heat-related deaths fall into this age group, with the effect being about 35% higher among women than among men. As a result, an aging population winds up in a higher number of excess deaths even without a further shift in the frequency of extreme temperature events, as the net effect of individual heat waves is effectively increasing. This effect has consequences when thinking about appropriate steps for climate policies even though all forecasts are based on hypothetical scenarios that compound the uncertainties involved and limit the precision of the resulting policy-recommendations (Weitzman, 2011). While the actual outcome might look different, the conclusions drawn are nevertheless important to shape current and future climate polices (McMichael et al., 2006; Huang et al., 2011).

Robustness

The impact of extreme temperature events on human mortality can also be estimated using two other approaches that address the seasonal variation in mortality rates. One is a fixed effects model using month- and year-fixed effects; the other is a frequency domain model using a combination of sine and cosine functions in conjunction with an ideal band filter. Since singular systems analysis would use sine and cosine functions as its orthogonal signal components if this would be optimal, there is no reason to assume that the frequency domain model would outperform it. Given that the fixed effects models operates strictly in the time domain and not in the frequency domain, the same argument cannot be made here. Both akaike and bayesian information criterions as well as leave-one-out cross validation indicate that the identification strategy using singular systems analysis performs –on average– better than the approach using a fixed effects model. This confirms the results from chapter 1 and shows that the approach presented also provides better results under more complex specifications. Details are provided in tables A-4, A-5, and A-6 in the appendix.

Robine et al. (2008) provide estimates of excess deaths for parts of Europe during a heatwave in 2003. A total of nine countries of their analysis overlap with the analysis presented here. This can be used to evaluate the actual performance of the macro-level approach. The following table 2.1 compares the hospital level results of Robine et al. (2008) with the estimates from this chapter.

month	excess deaths during summer 2003 (this chapter)	(Robine et al., 2008)
June	12,393	12,387
July	10,008	10,456
August	43,695	42,545
September	683	4,816
total	66,779	70,188

Table 2.1: **Heat-caused month-by-month excess mortality during Summer 2003 in Europe.** The approach using singular systems analysis is the described in depth in the first chapter; Robine et al. (2008) use hospital-level data.

As can be seen, the estimates derived from the approach using spectrum systems analysis are very close to the actual numbers except for the month of September. A country-by-country comparison can be found in the appendix in table A-1. Note further that the estimates of heat-caused deaths here are closer to the actual numbers than in chapter 1 of this dissertation. The reason for this is that the first chapter does not differentiate heat waves based on their intensity, while this second chapter does. When looking at the underlying climate data, the heat in Europe was the most intense during August, but not very intense during September. This is also indicated by the estimates of excess deaths of the macro level model. The gap between the macro level estimates and the numbers by Robine et al. (2008) thus suggests that the latter is overestimating the impact of heat waves on mortality.

Implications for Climate Change Mitigation

Leaving climate change unchecked will increase excess mortality substantially by the end of the century. This will have a substantive effect on the economy. Following the best practices for valuing a statistical life (OECD, 2012), the average current yearly economic damage of extreme temperature events is about 0.8% (±0.4%) of total GDP across the 27 surveyed countries. Investing in climate change mitigation would not only reduce the future costs associated with this loss of life, but also allow to reap co-benefits from the simultaneous reduction of greenhouse gases and other pollution (K. R. Smith and Haigler, 2008), particularly if the transportation sector is targeted (Younger, Morrow-Almeida, Vindigni, and Dannenberg, 2008). This strategy would also alleviate the pressure for adaptation that the Mediterranean countries will face in the future under any scenario of climate change.

Implications for Climate Change Adaptation

For some countries, adaptation to the impacts of heat waves will be an important –irrespective of the specific level of climate change– as heat waves will become more frequent and more intense. Adaptation can take place either through physiological change due to exposure, behavioral change, or physical changes. Behavioral adjustments to extreme temperatures have been found (Graff Zivin and Neidell, 2014) and could potentially assume many shapes. Further evidence suggests that the mechanism of physical change –such as via the use of air conditioning units– is important as well (Barreca et al., 2016). Air conditioning reduces the vulnerability to extreme heat (Bouchama and Knochel, 2002; Reid et al., 2009) and might become even more important with increasing urbanization (Luber and McGeehin, 2008), yet it is not widely used in many European countries (Pezzutto et al., 2016). Overall, the available data on adaptation are limited, rendering the analysis of its impact difficult (Deschenes, 2014). Nevertheless, studies have shown that at least some adaptation has already taken place, yet not to the highest possible degree (Barreca et al., 2015). This remaining potential for adaptation suggests that this paper's forecasts of excess mortality are upper bound estimates as some additional level of adaptation can be expected in the future.

Conclusions

Episodes of extreme temperatures are a major driver of human mortality in Europe, particularly for people aged 50 and above. Countries are not affected uniformly — in future, with a changing climate, the challenges that individual countries face will diverge tremendously: Scandinavia and some parts of Eastern Europe will not experience a tremendous increase in heat-related mortality even under a scenario of severe global warming. In contrast, the nations bordering the Mediterranean sea –particularly Greece, Italy, and Spain– will be negatively affected already early on under moderate climate change. This means that a roadmap for climate change adaptation in Europe should target these vulnerable states early on in order to prevent unnecessary excess deaths..

In addition to adaptation, mitigation remains an important part for European climate policy. If it is feasible to contain the level of greenhouse gases in the atmosphere within the RCP 4.5-scenario, the large majority of European countries will not be negatively affected by the change in the local climatology; in contrast, some countries could even benefit from drastically reduced cold spell-related mortality.

In conclusion, this means that the loading of the climate dice does not inevitably mean a threat to public health in form of an increase of net mortality. However, excess loading does pose a tremendous danger and should accordingly be avoided.

Chapter 3

Explicit Communication of Uncertainty: Increasing Cooperation in Climate Policy

Failure in international coordination on climate change mitigation policies can possibly result in high losses due to a sudden shift in climate-sensitive environmental systems. The uncertainty associated with these potential losses is usually only addressed implicitly when discussing the costs and benefits of climate change policies using the usual expected utility framework. However, explicit communication might increase cooperation across political actors.

Here, I analyze this subject experimentally. Using equivalent common pool games, the difference between masking uncertainty behind an expected utility framework and making it explicit is explored.

The experiment shows that communication of uncertainty matters. The average level of contribution in a common pool game increases significantly when uncertainty is communicated, increasing average returns. This finding suggests that climate change mitigation strategies could increase adoption if the uncertainty associated with climate change is made explicit.

3.1 Motivation

Climate change is one of the biggest challenges of our time: Countries need to cooperate and to reduce global CO_2-emissions. As is the case in social dilemma situations, cooperation and mutual abatement are hard to reach given that collective interests do not align with private interests — accordingly, so far, no effective climate policy regime has been created. In contrast, instead of working towards the Pareto-optimal situation of mutual climate change mitigation, some countries start to focus on the adoption of –individually rational– climate change adaptation measures.

Due to its nature, climate change poses a slightly different case than other social dilemma situations: The negative effects of climate change do not necessarily take place incrementally. Scientific evidence (Clark, Pisias, Stocker, and Weaver, 2002; Dakos et al., 2008; Lenton et al., 2008) suggests that abrupt changes with catastrophic consequences can occur – and have occurred – after reaching a certain, currently unknown, threshold in the atmospheric CO_2-level. This results in a damage function that is characterized by high-impact, low-probability events (Weitzman, 2009, 2011). This should make the possibility of abrupt climate change a focal point for policy makers (Alley et al., 2003) and thus also of those who study the emergence of international climate governance.

Notwithstanding this, the costs of climate change tend to be presented to policy makers without explicit acknowledgement of this possibility, but rather using expected values (see e.g. Fankhauser, 1994). An early example of this is DICE (Dynamic Integrated model of Climate and the Economy). This is one of the most prominent integrated assessment models on climate change policies, developed by Nordhaus (1994). While Nordhaus devotes a lot of attention to the issue of uncertainty when discussing his model, uncertainty is not made explicit in the output of the model. Generally, there is a high degree of variance in estimates across models (Tol, 2005), though the individual models do not necessarily acknowledge this.

It is no surprise that this the situation is comparable when it comes to policy reports. While the 2017 Economic Report of the President acknowledges the importance of possible climate catastrophes, it fails to actually discuss them and instead relies on expected costs (*Economic Report of the President*, 2017).

Another example for this can be found in the executive summary of the Stern report. In this work –arguably the most influential economic analysis of the costs of climate change to date– Stern chooses to present his results within an expected utility framework:

> Using the results from formal economic models, the Review estimates that if we don't act, the overall costs and risks of climate change will be equivalent to losing at least 5% of global GDP each year, now and forever. If a wider range of risks and impacts is taken into account, the estimates of damage could rise to 20% of GDP or more. (Stern, 2006, p. vi)

Similarly, the latest IPPCC chooses to identify key risks based on both probability and impact:

> Risk is often represented as the probability of occurrence of hazardous events or trends multiplied by the magnitude of the consequences if these events occur. Therefore, high risk can result not only from high probability outcomes but also from low probability outcomes with very severe consequences. (IPCC, 2014c, p. 36)

When presenting and summarizing key risks in its synthesis report, it does not differentiate between low-impact, high-probability and high-impact, low probability events (see IPCC, 2014c, p. 65, fig. 2.4), thus implicitly assuming that both types of risk are to be treated in the same manner.

The question is whether or not a more differentiated way of communicating the uncertainty of climate change impacts would lead to a more cooperative reaction from policy makers. Given the nature of climate change –with its major impacts expected in the distant future– a natural experiment might not be the way to find an answer. This makes the case for a laboratory experiment.

Behavioral economics in general might play an important role when it comes to communicating and designing climate change policies (see e.g. Gowdy, 2008) as well as managing common pool resources (Ostrom, 2006). Particularly laboratory experiments allow controlled variation and thus causal inference (Falk and Heckman, 2009). Some experimental approaches have included catastrophic thresholds in contribution games (Barrett and Dannenberg, 2012; Barrett, 2013; Barrett and Dannenberg, 2014b; Dannenberg, Löschel, Paolacci, Reif, and Tavoni, 2015), focusing on impact and threshold uncertainty. Barrett and Dannenberg (2014a) compare gradual with abrupt climate change in a one-shot contribution game and find that contributions are higher in case of abrupt climate change.

Here, something similar is done using symmetric contribution games. The first game is based on the standard expected utility framework, while the second includes a degree of uncertainty. In contrast to the work by Barrett and Dannenberg (2014a) where the noncooperative outcome is not hold constant across treatments, both treatments here are equivalent in expectation. The experiment is thus both a complement and an extension to existing literature and therefore a potentially important contribution to both economic theory and global environmental governance.

While the focus of this experimental paper is catastrophic climate risk, the conclusions drawn from it can be used for similar social dilemma situations. As Scheffer, Carpenter, Foley, Folke, and Walker (2001) suggest, a variety of ecosystems such as coral reefs, woodlands, and deserts might react with sudden shifts when exposed to gradual change in environmental parameters. Rockström et al. (2009) link a change in key environmental variables to many of these shifts.

Knowledge about the effects of risk communication on cooperation might thus be needed for sustainably managing human interaction with a broad range of complex environmental systems.

3.2 Methodology

The experiment is based on two single-shot public goods games using groups of four. One game is a standard version of the game, the other is a non-standard version, where returns depend on meeting an unknown threshold that is determined by chance. The first game, the standard game, represents the expected utility representation of climate change — the costs of non-cooperation are linear, there are no unknowns, and there is no abrupt response. The second game, the uncertainty game, represents the uncertainty representation of climate change — a high-impact event is triggered if an unknown minimum level of cooperation is not met.

The expected payoffs in both treatments are the same. There is a single Nash equilibrium — to contribute zero to the public good. Players should hence contribute the same amount, that is zero. This forms the null and alternative hypotheses: If communicating the possible catastrophes matters, there should be a higher level of cooperation in the uncertainty treatment than in the standard game. One possible explanation is standard risk aversion, which is extensively discussed by Rabin and Thaler (2001). In the uncertainty game, participants that are risk averse, need to make a trade-off between maximizing their earnings and minimizing the potential risk from the catastrophe within their objective function. Hence, risk averse participants should contribute more in the uncertainty version of the game than in the standard version.

In the laboratory experiment, participants are drawn from the student body of Columbia University (using the recruitment-software ORSEE, see Greiner, 2015) and interact with each other using computer terminals (programmed with the software zTree, see Fischbacher, 2007). Each participant plays both treatments 20 times each, with random rematching of participants between each round. Some participants play the standard version first, while others play the uncertainty version first. This allows to control for treatment order effects and to increase the statistical power, thus combining the benefits of a between- with the benefits of a within-subjects design following Charness, Gneezy, and Kuhn (2012). In addition to the two common pool games, participants play a risk elicitation game using the multiple price list method following Holt and Laury (2002) (see appendix, table A-7). Finally, A survey at the end of the experiment (see appendix, table A-8) allows to draw more inferences about the impact of socio-economic factors as well as about the participants' motivations.

Expected Utility Representation

The standard game –the expected utility representation of climate change– is a single-shot public goods game played with groups of four. The budget per participant is ten token. The full budget can be invested towards the common pool. After everyone has decided on the level of their contribution, q_i, participants receive 0.5 token per token in the pool. In addition, participants can keep the remaining token in their budget. The payoff-function for individual i looks as follows:

$$\pi_i = 10 - q_i + 0.5 \cdot \sum_{n=1}^{4} q_n$$

$$q \in \{0, \ldots, 10\}$$

If nobody contributes to the common pool, the individual payoff is 10 token; if everybody contributes the maximum, the individual payoff is twenty token. Accordingly, the social optimum is to contribute the maximum amount of token, whereas the unique Nash equilibrium is to not contribute at all.

Uncertainty Representation

The second treatment –the uncertainty representation of climate change– is also single-shot public goods game played with groups of four. The budget per participant is thirty token. Up to ten token can be invested towards the common pool. Participants can keep the remaining token from their budget. Here, participants do not receive returns on the pool — contributions to the pool reduce the risk of a catastrophe. If the catastrophe happens, all participants suffer a loss of twenty token. The chance of this happening is 0% if all four group members invest the maximum of ten token each. It is 100% if the total group contribution is zero and changes linearly in between. The function for expected payoffs of individual i looks as follows:

$$E\pi_i = 30 - q_i - P(C) \cdot 20$$
$$P(C) = 1 - \frac{1}{40} \cdot \sum_{n=1}^{4} q_n$$
$$q \in \{0, \ldots, 10\}$$

Again, as in the first treatment, if nobody contributes to the common pool, the individual payoff is 10 token; if everybody contributes the maximum, the individual payoff is twenty token.

This means that the payoffs for both the non-cooperative as well as the full cooperative outcome are held the same across both treatments. Accordingly, the dominant strategy for a player –no contribution to the pool– is also the same in either treatment. Further, as both games have the same constant marginal per capita returns, differences in behavior across games are not expected.

3.3 Results

The experiment was conducted in six sessions with a total of 100 participants. In three sessions with 52 participants the expected utility version of the treatment was played before the uncertainty version; in three other sessions with 48 participants, the treatment order was reversed.

Impact on Contributions to the Common Pool

While both treatments are equivalent in expectation, the behavior that participants showed in the uncertainty game was in stark contrast to their behavior in the standard game ($p < 0.01$).

treatment	mean group contribution	modal group contribution	range of group contribution
standard game	12.1	10	0 – 40
uncertainty game	24.0	20	5 – 38

Table 3.1: **Summary statistics of experimental results.** Mean and modal group contributions are provided for each treatment as well as the range of group contributions.

On average, the difference in the average individual contribution is 2.97 higher in the uncertainty representation than in the expected utility representation. That means, with an average individual contribution of 3.03 in the standard game, the contributions in the uncertainty game are over 98% higher. In terms of group behavior, this translates into higher average group contributions and thus also higher individual payoffs. Figure 3.1 shows how this difference in behavior develops over time:

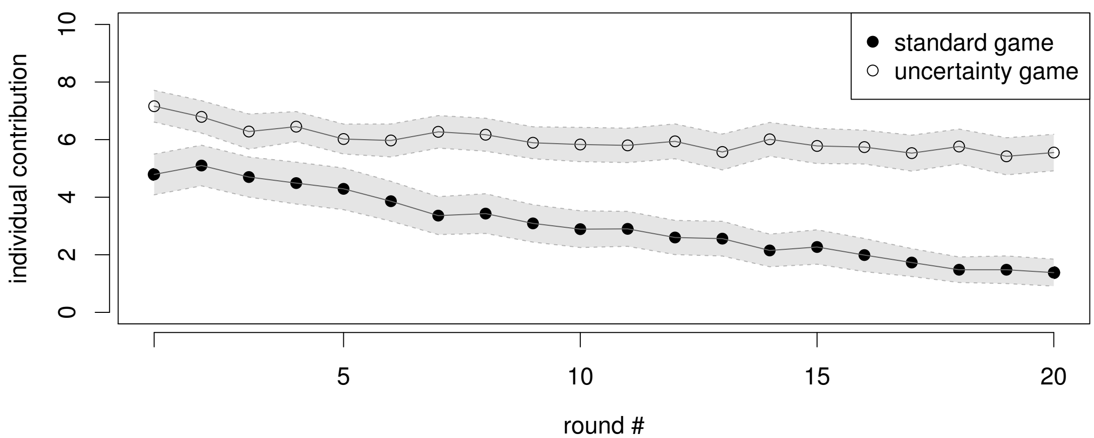

Figure 3.1: **Average individual contribution by treatment and round.** The plot shows the average individual contribution with the 95% confidence interval for both the standard game and the uncertainty variation of the game for each round.

With each round, the difference between the average individual contribution in each treatment increases. In the expected utility framework, the average individual contribution decreases on average by 0.20 in each round, whereas the decline in the uncertainty treatment is barely noticeable with only 0.06, that is less than one third of the decline of the standard game.

For later rounds of the expected utility game, the average contribution converges to zero, that is towards the dominant strategy. In contrast, the level of individual contributions in the uncertainty representation stays comparatively high.

When only looking at the second half of each treatment, that is when only considering round 11 to 20, the difference between the two treatment becomes even more apparent. There, the average individual contribution in the standard game decreases on average by 0.17 in each round, whereas the average contribution in the uncertainty game remains constant around 5.71. This result is insofar interesting as contributions towards a common pool usually tend to decrease over time in an experimental setting.

This indicates that the uncertainty representation leads the participants towards an attractor approximately at the middle between social optimum and Nash equilibrium. This behavior in the uncertainty game is consistent irrespective of treatment order. Further, this also means that participants are not confused about the game or its solution as their behavior does not change over time.

Treatment Order Effects

Treatment order does not explain the observed difference as it persists when disaggregating the experimental data based on which treatment was played first. As figure 3.2 shows, the difference between the standard game and the uncertainty game remains. The difference between the average level of contribution increases in both cases with the number of periods. On average it is 3.08 when the respective treatment is being played first, and it is 2.86 when the respective treatment is being played second. There is no significant difference in the level of contribution between the individual games being played first and being played second.

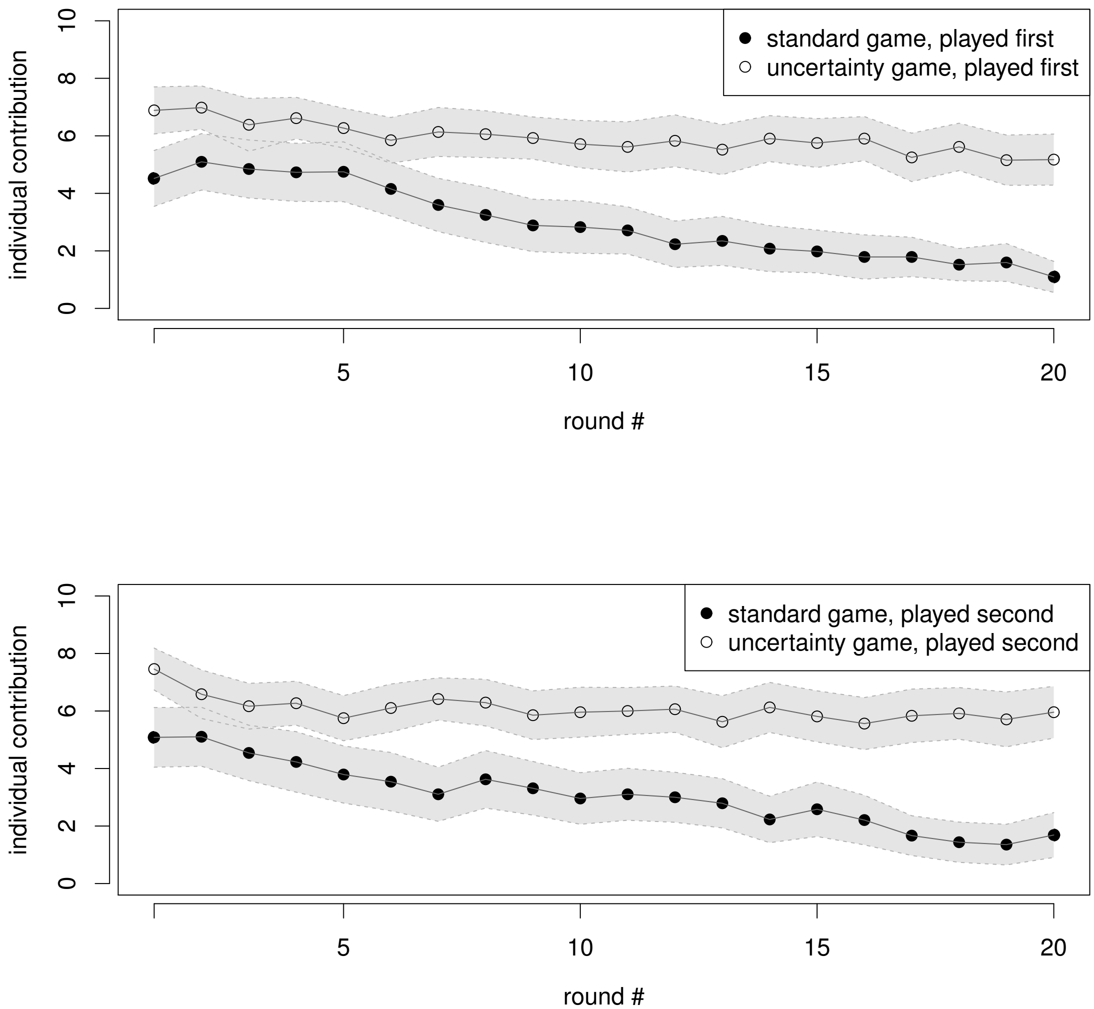

Figure 3.2: **Average individual contribution by treatment, treatment order, and round.** The first plot shows the average individual contribution with the 95% confidence interval for both the standard game and the uncertainty game being played first, the second plot shows the average individual contribution with the 95% confidence interval for both the standard game and the uncertainty variation of the game being played second.

When the standard game is being played first, the average individual contribution decreases by 0.21 per round — when it is being played second, the decrease is 0.18. This trend is very similar when only looking at rounds 11 to 20. There, with the standard game being played first, the decrease is 0.15 and, with the standard game being played second, 0.20. The situation looks very different for the uncertainty game. When this game is being played first, this decrease is 0.05; when it is being played second, it is 0.08. When only looking at rounds 11 to 20, there is not significant change in the average individual contribution.

Further results

Experiencing a loss in the uncertainty game has an impact on the following average individual contribution (0.45, $p < 0.01$). The effect size is too small to explain the differences in average contribution between the standard game and the uncertainty game, especially since the loss was only experienced in about 30% of all rounds and as there is already a difference in behavior from the first round on.

Neither stated nor revealed risk preferences have a significant impact on the level of contribution in either treatment. This means that risk averse individuals do not contribute more than risk loving individuals and that the difference in average contribution across treatments cannot be explained with risk aversion of the individual. Calculating the constant relative risk aversion revealed through the difference in contribution across the two treatments for each individual, substantiates this finding further. Comparing it to the results from the multiple price list method, indicates that 89 participants should have contributed less in the uncertainty game than they actually did. In contrast, only five participants contributed more than they were expected based on their level of risk aversion. For six participants, the analysis was inconclusive as they did not behave rational in the risk elicitation game. Keeping this result in mind, 92% of the participants stated that their willingness to accept risks was at least somewhat important in determining their level of contribution.

When it comes to fairness, the results are similar. It did also not play a decisive role, but 77% of participants considered fairness an at least somewhat important issue in the experiment.

There is no indication that age, gender, major, or other socio-economic factors played a decisive role. After the experiment, 60% of the participants indicated that they preferred the uncertainty game, while 32% preferred the standard game. As average earnings for the uncertainty game were higher than for the standard game, this makes intuitive sense.

3.4 Discussion

The results demonstrate that the representation of uncertainty matters when it comes to individual contributions towards a common good. Making uncertainty explicit makes cooperation more obtainable. This finding is not the result of risk aversion, which is consistent with Barrett and Dannenberg (2014a), who also find that risk aversion does not influence the level of contribution.

Perception of Others' Likelihood to Contribute

As risk aversion does not play a role for the increased level of contribution in the uncertainty representation when compared to the expected utility representation, there has to be a different explanation. One possible reason is that –while individual risk aversion does not matter– expectations about others' behavior does. Participants might be guided by a preference for fairness and might try to avoid unequal outcomes. Comments by participants that were collected with a questionnaire (see appendix, table A-8) after the experiment support this hypothesis and indicate that participants thought that others would be more willing to contribute when facing uncertainty:

> [I contributed more b]ecause it's likely that the [uncertainty game] makes people want to collaborate.

> I felt more inclined to contribute greater amounts [in the uncertainty game] and I know others did as well.

> [There was] more incentive to cooperate [in the uncertainty game].

> It seemed like the risk of failure [in the uncertainty game] incentivized greater cooperation.

> People [contributed] more because there was more at stake for them [in the uncertainty game].

It thus seems as if participants make rather assumptions about others and adjust their own behavior accordingly. Results that are similar to this, though not related to public goods games, are discussed by Goeree and Holt (2001). Another possible explanation might be inequity aversion (see Fehr, Naef, and Schmidt, 2006). Participants expect other participants to contribute more in the uncertainty game than in the standard game and thus contribute more themselves.

Interestingly enough, some participants preferred the standard game, arguing to have more control over their own payoff that way:

> I didn't have to worry as much about the other participants [in the standard game].

> I have much more control [in the standard game].

> [The uncertainty game] relied heavily on the actions of others for success, thus making it more unpredictable.

There is no significant difference in behavior between the participants that prefer the standard game to those that prefer the uncertainty game when playing the uncertainty game. On the other hand, on average, participants that prefer the standard game contribute less ($p < 0.01$) than those that prefer the uncertainty game when playing the standard game. This result suggests that the uncertainty representation can support a positive level of cooperation, irrespective of the type of participants involved.

One open question –that this study is not able to address– is the question, whether group size has an noticeable and meaningful impact on this effect. It is conceivable, that individuals perceive a decreasing likelihood of others to contribute with increasing size. Literature finds that this is not the case if the increase in group size does not go along with a decrease in marginal returns from contributing (Isaac and Walker, 103). In contrast, group size might even be beneficial (Isaac, Walker, and Williams, 1994), at least if the marginal returns from contributing are rather low (Nosenzo, Quercia, and Sefton, 2015). The caveat here is, that group size might have a different effect on the uncertainty representation than on the expected utility representation. Thus, more research on the topic is needed.

Conclusions

Taken together, the experimental results make the case for a paradigm shift in communicating the uncertainties associated with climate change and climate mitigation policies. By making the uncertainty evident, individuals are nudged to make new assumptions about each others' behavior and voluntarily adjust their own behavior accordingly. The result is more cooperation, higher individual returns, and a move towards the social optimum.

This result is of significance for the creation of international climate policy regimes.

It suggests that uncertainty should be discussed in executive summaries and that it is not sufficient to hide it behind the single number that is expected costs.

Conclusion

This work deals with different aspects of the economics of climate change in three essays. The first essay discusses the possibility to use data of low spatial and temporal resolution to estimate the impact of heat waves on human mortality. The second essay uses the methodology developed in the first essay to assess the impact of temperature extremes on mortality rates in Europe under two climate change scenarios. The last essay explores how uncertainty –such as about the impact of temperature extremes– needs to be framed in order to promote cooperation.

Three main results can be drawn from this work: First, singular spectrum analysis is a valid tool that can be used to gain sufficient information on excess mortality in order to make plausible inferences on the effects of extreme temperature events on human mortality. As a result, the analysis of climate change impacts on public health can be extended to geographic areas where no detailed health data are available. Thus, a more comprehensive idea of the impacts of climate change can be gained. Second, climate change impacts are not uniform and can –under certain scenarios– produce winners and losers. More specifically speaking, climate change –if contained to a small rise in average temperatures– can have a negative net impact on mortality in some European countries due to a decrease in cold spells. In contrast, unrestricted climate change can lead to a large increase in net mortality across all examined countries as a result of increasingly frequent heat waves. This means that –from a public health perspective for Europe– climate change should be mitigated to some degree.

Third, uncertainty associated with climate change impacts needs to be communicated explicitly if the goal is to increase international cooperation on climate change mitigation policies. Social dilemma situations are perceived differently when discussing uncertainty openly rather than using an expected utility framework. This means that uncertainty needs to be featured more prominently in the executive summaries of assessment reports on climate change impacts.

These results are important for two major reasons. For one, extending the analysis of climate change impacts beyond those countries for which there are very detailed data, allows to improve our understanding of the heterogeneity in impacts as well as to gain more knowledge about the interaction between impact and socio-economic context. In turn, this makes it possible to design better adaptation policies and to direct funds towards the regions that will be affected the most. For another, enriching pure game theory with insights from laboratory experiments –thus considering behavioral effects– allows for far better, much more effective design of climate change mitigation treaties.

While this work primarily focuses on the health impacts of climate change as well as on how to deal with the associated uncertainty, it has wider implications; some of the conclusions drawn can be applied to other challenges of sustainable development. On the one hand, there is a lack of detailed data for many countries. At least when it comes to phenomena that are subject to cyclic fluctuations –such as weather patterns and certain vector-born diseases– singular spectrum analysis can be a helpful complement to other approaches. While not a replacement for analyses based on micro-level data, it can guide and inform policy decisions until better data are available. On the other hand, environmental policies often face a high degree of uncertainty due to he complex nature of human-environment systems. Here, when different parties are needed to cooperate, the communication of uncertainty matters. Thus, explicit communication of uncertainty can help to implement environmental policies other than those targeting at climate change mitigation.

In conclusion, there are many open questions on economics of climate change. Some of them are explored in the context of this work. The gained results help complement existing approaches and possibly support the design and implementation of better climate change policies.

Bibliography

Adger, W. N. (1999). Social vulnerability to climate change and extremes in coastal vietnam. *World Development*, *27*(2), 249–269.

Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Klein Tank, A. M. G., ... Vazquez-Aguirre, J. L. (2006). Global observed changes in daily climate extremes of temperature and precipitation. *Journal Of Geophysical Research: Atmospheres*, *111*(D5).

Alley, R. B., Marotzke, J., Nordhaus, W. D., Overpeck, J. T., Peteet, D. M., Pielke Jr, R. A., ... Wallace, J. M. (2003). Abrupt climate change. *Science*, *299*(5615), 2005–2010.

Analitis, A., Katsouyanni, K., Biggeri, A., Baccini, M., Forsberg, B., Bisanti, L., ... Michelozzi, P. (2008). Effects of cold weather on mortality: results from 15 european cities within the phewe project. *American Journal of Epidemiology*, *168*(12), 1397–1408.

Anderson, G. B. & Bell, M. L. (2009). Weather related mortality: how heat, cold, and heat waves affect mortality in the united states. *Epidemiology*, *20*(2), 2005–213.

Anderson, G. B. & Bell, M. L. (2011). Heat waves in the united states: mortality risk during heat waves and effect mofidication by heat wave characteristics in 43 u.s. communities. *Environmental Health Perspectives*, *19*(2), 210–218.

Åström, D. O., Forsberg, B., & Rocklöv, J. (2011). Heat wave impact on morbidity and mortality in the elderly population: a review of recent studies. *Maturitas*, *69*(2), 99–105.

Baccini, M., Biggeri, A., Accetta, G., Kosatsky, T., Katsouyanni, K., Analitis, A., ... Michelozzi, P. (2008). Heat effects on mortality in 15 european cities. *Epidemiology*, *19*(5), 711–719.

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica*, *77*(4), 1229–1279.

Ballester, F., Corella, D., Pérez-Hoyos, S., Sáez, M., & Hervàs, A. (1997). Mortality as a function of temperature. a study in valencia, spain, 1991-1993. *International Journal Of Epidemiology*, *26*(3), 551–561.

Ballester, J., Rodo, X., Robine, J.-M., & Herrman, F. R. (2016). European seasonal mortality and influenza incidence due to winter temperature variability. *Nature Climate Change*. doi:10.1038/nclimate3070

Barnett, A. G. (2007). Temperature and cardiovascular deaths in the us elderly: changes over time. *Epidemiology*, *18*(3), 369–372.

Barnett, A. G., Hajat, S., Gasparrini, A., & Rocklöv, J. (2012). Cold and heat waves in the united states. *Environmental Research*, *112*, 218–224.

Barreca, A. (2012). Climate change, humidity, and mortality in the united states. *Journal Of Environmental Economics And Management*, *63*(1), 19–34.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2015). Convergence in adaptation to climate change: evidence from high temperatures and mortality, 1900–2004. *American Economic Review: Papers & Proceedings*, *105*(5), 247–251.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: the remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal Of Political Economy*, *124*(1), 105–159.

Barrett, S. (2013). Climate treaties and approaching catastrophes. *Journal of Environmental Economics and Management*, *66*(2), 235–250.

Barrett, S. & Dannenberg, A. (2012). Climate negotiations under scientific uncertainty. *Proceedings Of The National Academy Of Sciences*, *109*(43), 17372–17376.

Barrett, S. & Dannenberg, A. (2014a). Negotiating to avoid 'gradual' versus 'dangerous' climate change: an experimental test of two prisoners' dilemmas. In T. Cherry, J. Hovi, & D. M. McEvoy (Eds.), *Towards a new climate agreement: conflict, resolution, and governance* (pp. 61–75). Routledge: London.

Barrett, S. & Dannenberg, A. (2014b). Sensitivity of collective action to uncertainty about climate tipping points. *Nature Climate Change*, *4*(1), 36–39.

Bouchama, A. & Knochel, J. P. (2002). Medical progress – heat stroke. *New England Journal Of Medicine*, *346*(25), 1978–1988.

Burger, E. H., Groenewald, P., Bradshaw, D., Ward, A. M., Yudkin, P. L., & Volmink, J. (2012). Validation study of cause of death statistics in cape town, south africa, found poor agreement. *Journal Of Clinical Epidemiology*, *63*(3), 309–316.

Changnon, S. A., Kunkel, K. E., & Reinke, B. C. (1996). Impacts and responses to the 1995 heat wave: a call to action. *Bulletin Of the American Meteorological Society*, *77*(7), 1497–1506.

Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: between-subject and within-subject design. *Journal Of Economic Behavior & Organization*, *81*(1), 1–8.

Clark, P. U., Pisias, N. G., Stocker, T. F., & Weaver, A. W. (2002). The role of the thermohaline circulation in abrupt climate change. *Nature*, *415*(6874), 863–869.

Conti, S., Meli, P., Minelli, G., Solimini, R., Toccaceli, V., Vichi, M., ... Perini, L. (2005). Epidemiologic study of mortality during the summer 2003 heat wave in italy. *Environmental Research*, *98*(3), 390–399.

Currie, J. & Neidell, M. (2005). Air pollution and infant health: what can we learn from california's recent experience? *The Quarterly Journal Of Economics*, *120*(3), 1003–1030.

Dakos, V., Scheffer, M., van Nes, E. H., Brovkin, V., Petoukhov, V., & Held, H. (2008). Slowind down as an early warning signal for abrupt climate change. *Proceedings Of The National Academy Of Sciences*, *105*(38), 14308–14312.

Dannenberg, A., Löschel, A., Paolacci, G., Reif, C., & Tavoni, A. (2015). On the provision of public goods with probabilistic and ambiguous thresholds. *Environmental and Resource Economics*, *61*(3), 365–383.

Deschenes, O. (2014). Temperature, human health, and adaptation: a review of the empirical literature. *Energy Economics*, *46*, 606–619.

Deschenes, O. & Greenstone, M. (2011). Climate change, mortality, and adaptation: evidence from annual fluctuations in the us. *American Economic Journal: Applied Economics*, *3*, 152–185.

Deschenes, O., Greenstone, M., & Guryan, J. (2009). Climate change and birth weight. *American Economic Review: Papers & Proceedings*, *99*(2), 211–218.

Díaz, J., García, R., López, C., Linares, C., Tobías, A., & Prieto, L. (2005). Mortality impact of extreme winter temperatures. *International Journal Of Biometeorology*, *49*(3), 179–183.

Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., & Mearns, L. O. (2000). Climate extremes: observations, modeling, and impacts. *Science*, *289*(5487), 2068–2074.

Elguindi, N., Rauscher, S. A., & Giorgi, F. (2013). Historical and future changes in maximum and minimum temperature records over europe. *Climatic Change*, *117*(1), 415–431.

Elsner, J. B. & Tsonis, A. A. (1996). *Singular spectrum analysis*. Plenum Press.

Epstein, Y. & Moran, D. S. (2006). Thermal comfort and the heat stress indices. *Industrial Health*, *44*(3), 388–398.

Eurostat. (2015). *Database*. Retrieved from http://ec.europa.eu/eurostat/data/database

Eurostat & EFGS. (2015). *Geostat 2011 v2*. Retrieved from http://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography

Falk, A. & Heckman, J. J. (2009). Lab experiments are a major source of knowledge in the social sciences. *Science*, *326*(5952), 535–538.

Fankhauser, S. (1994). The social costs of greenhouse gas emissions: an expected value approach. *The Energy Journal*, *15*(2).

Fehr, E., Naef, M., & Schmidt, K. M. (2006). Inequality aversion, efficiency, and maximin preferences in simple distribution experiments: comment. *The American Economic Review*, *96*(5), 1912–1917.

Fischbacher, U. (2007). z-Tree: zurich toolbox for ready-made economic experiments. *Experimental Economics*, *10*(2), 171–178.

Fischer, E. M. & Knutti, R. (2015). Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. *Nature Climate Change*, *5*(6), 560–564.

Fouillet, A., Rey, G., Laurent, F., Pavillon, G., Bellec, S., Guihenneuc-Jouyaux, C., … Hémon, D. (2006). Excess mortality related to the august 2003 heat wave in france. *International Archives Of Occupational And Environmental Health*, *80*(1), 16–24.

Ghil, M., Allen, M. R., Dettinger, M. D., Ide, K., Kondrashov, D., Mann, M. E., … Yiou, P. (2002). Advanced spectral methods for climatic time series. *Reviews Of Geophysics*, *40*(1).

Goeree, J. K. & Holt, C. A. (2001). Ten little treasures of game theory and ten intuitive contradictions. *American Economic Review*, *91*(5), 1402–1422.

Gore, A. (2013). *Earth in the balance: forging a new common purpose* (Revised Edition). Routledge: London.

Gowdy, J. M. (2008). Behavioral economics and climate change policy. *Journal Of Economic Behavior & Organization*, *68*(3-4), 632–644.

Graff Zivin, J. & Neidell, M. (2014). Temperature and the allocation of time: implications for climate change. *Journal Of Labor Economics*, *32*(1), 1–26.

Granger, C. W. J. & Hatanka, M. (1964). *Spectral analysis of economic time series (psme-1)*. Princeton University Press: Princeton, NJ.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal Of The Economic Science Association*, *1*(1), 114–125.

Grize, L., Huss, A., Thommer, O., Schindler, C., & Braun-Fahrländer, C. (2005). Heat wave 2003 and mortality in switzerland. *Swiss Medical Weekly*, *135*(13-14), 200–2005.

Gronlund, C. J., Berrocal, V. J., White-Newsome, J., Conlon, K. C., & O'Neill, M. S. (2015). Vulnerability to extreme heat by socio-demographic characteristics and area green space among the elderly in michigan, 1990–2007. *Environmental Research*, *136*, 449–461.

Gronlund, C. J., Zanobetti, A., Wellenius, G. A., Schwartz, J. D., & O'Neill, M. S. (2016). Vulnerability to renal, heat and respiratory hospitalizations during extreme heat among u.s. elderly. *Climatic Change*, *136*(3), 631–645.

Hajat, S., Kovats, R. S., & Lachowycz, K. (2007). Heat-related and cold-related deaths in england and wales: who is at risk? *Occupational & Environmental Medicine*, *64*(2), 93–100.

Hansen, J., Sato, M., & Ruedy, R. (2012). Perception of climate change. *Proceedings Of The National Academy Of Sciences*, *109*(37), 2415–2423.

Hassani, H. (2007). Singular spectrum analysis: methodology and comparison. *Journal of Data Science*, *5*(2), 239–257.

Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., D, J. P., & M, N. (2008). A european daily high-resolution gridded data set of surface temperature and precipitation for 1950 - 2006. *Geophysical Research: Atmospheres*, *113*(D20).

Helweg-Larsen, K. (2011). The danish register of causes of death. *Scandinavian Journal Of Public Health*, *39*(7), 26–29.

Holt, C. A. & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655.

Huang, C., Barnett, A. G., Wang, X., Vaneckova, P., FitzGerald, G., & Tong, S. (2011). Projecting future heat-related mortality under climate change scenarios: a systematic review. *Environmental Health Perspectives*, *119*(12), 1681–1690.

Huynen, M. M., Martens, P., Schram, D., Weijenberg, M. P., & Kunst, A. E. (2001). The impact of heat waves and cold spells on mortality rates in the dutch population. *Environmental Health Perspectives*, *109*(5), 463–470.

IPCC. (2014a). AR5 WG I - climate change 2013: the physical science basis.

IPCC. (2014b). AR5 WG II - climate change 2014: impacts, adaptation, and vulnerability.

IPCC. (2014c). Climate change 2014: synthesis report. contribution of working groups i, ii, and iii to the fifth assessment report of the intergovernmental panel on climate change.

Isaac, R. M. & Walker, J. M. (103). Group size effects in public goods provision: the voluntary contributions mechanism. *The Quarterly Journal Of Economics*, *1*(179 – 199).

Isaac, R. M., Walker, J. M., & Williams, A. W. (1994). Group size and the voluntary provision of public goods: experimental evidence utilizing large groups. *Journal Of Public Economics*, *54*(1), 1–36.

Keatinge, W. R. & Donaldson, G. C. (2004). The impact of global warming on health and mortality. *Southern Medical Journal*, *97*(11), 1093–1099.

Kennelly, B., O'Shea, E., & Garvey, E. (2003). Social capital, life expectancy and mortality: a cross-national examination. *Social Science & Medicine*, *56*(12), 2367–2377.

Kovats, R. S. & Hajat, S. (2008). Heat stress and public health: a critical review. *Annual Review Of Public Health*, *29*, 41–55.

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., & Schellnhuber, H. J. (2008). Tipping elements in the earth's climate system. *Proceedings Of The National Academy Of Sciences*, *105*(6), 1786–1793.

Luber, G. & McGeehin, M. A. (2008). Climate change and extreme heat events. *American Journal Of Preventive Medicine*, *35*(5), 429–435.

Madrigano, J., Ito, K., Johnson, S., Kinney, P. L., & Matte, T. (2015). A case-only study of vulnerability to heat wave–related mortality in new york city (2000–2011). *Environmental Health Perspectives*, *123*(7), 672–678.

Marmor, M. (1975). Heat wave mortality in new york city, 1949 to 1970. *Archives Of Environmental Health*, *30*(3), 130–136.

McGeehin, M. A. & Mirabelli, M. (2001). The potential impacts of climate variability and change on temperature-related morbidity and mortality in the united states. *Environmental Health Perspectives*, *109*(2), 185–189.

McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: present and future risks. *Lancet*, *367*(9513), 859–869.

Meehl, G. A. & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, *305*(6586), 994–997.

Mensah, G. A. & Brown, D. W. (2007). An overview of cardiovascular disease burden in the united states. *Health Affairs*, *26*(1), 38–48.

Montgomery, D. C. (2009). *Design and analysis of experiments* (7th ed.). John Wiley & Sons.

Nordhaus, W. D. (1994). *Managing the global commons: the economics of climate change*. MIT Press: Cambridge, MA.

Nosenzo, D., Quercia, S., & Sefton, M. (2015). Cooperation in small groups: the effect of group size. *Experimental Economics*, *18*(1), 4–14.

OECD. (2012). *Mortality risk valuation in environment, health and transport policies.* OECD Publishing. doi:dx.doi.org/10.1787/9789264130807-en

O'Neill, M. S., Zanobetti, A., & Schwartz, J. (2005). Disparities by race in heat-related mortality in four us cities: the role of air conditioning prevalence. *Journal Of Urban Health*, *82*(2), 191–197.

O'Neill, M. S., Zanobetti, A., & Schwartz, J. (2003). Modifiers of the temperature and mortality association in seven us cities. *American Journal of Epidemiology*, *157*(12), 1074–1082.

Economic report of the president. (2017). Government Printing Office: Washington.

Ostro, B., Rauch, S., Green, R., Malig, B., & Basu, R. (2010). The effects of temperature and use of air conditioning on hospitalizations. *American Journal of Epidemiology*, *172*(9), 1053–1061.

Ostrom, E. (2006). The value-added of laboratory experiments for the study of institutions and common-pool resources. *Journal Of Economic Behavior & Organization*, *61*(2), 149–163.

Patz, J. A., Campbell-Lendrum, D., Holloway, T., & Foley, J. A. (2005). Impact of regional climate change on human health. *Nature*, *438*(7066), 310–317.

Pezzutto, S., Fazeli, R., De Felice, M., & Sparber, W. (2016). Future development of the air-conditioning market in europe: an outlook until 2020. *Wiley Interdisciplinary Reviews: Energy and Environment*. doi:10.1002/wene.210

Poumadère, M., Mays, C., Le Mer, S., & Blong, R. (2005). The 2003 heat wave in france: dangerous climate change here and now. *Risk Analysis*, *25*(6), 1483–1494.

Rabin, M. & Thaler, R. H. (2001). Anomalies: risk aversion. *The Journal Of Economic Perspectives*, *15*(1), 219–232.

Reid, C. E., O'Neill, M. S., Gronlund, C. J., Brines, S. J., Brown, D. G., Diez-Roux, A., & Schwartz, J. (2009). Mapping community determinants of heat variability. *Environmental Health Perspectives*, *117*(11), 1730–1736.

Riahi, K., Rao, S., Krey, V., Cho, C., Chrikov, V., Fischer, G., … Rafaj, P. (2011). Rcp 8.5–a scenario of comparatively high greenhouse gas emissions. *Climatic Change*, *109*(1), 33–57.

Robine, J.-M., Cheung, S. L. K., Le Roy, S., Van Oyen, H., Griffiths, C., Michel, J.-P., & Herrman, F. R. (2008). Death toll exceeded 70'000 in europe during the summer of 2003. *Comptes Rendus Biologies*, *331*(2), 171–178.

Robinson, P. J. (2001). On the definition of a heat wave. *Journal Of Applied Meteorology*, *40*(4), 762–775.

Rockström, J., Steffen, W., Noone, K., Persson, A., Chapin III, F. S., Lambin, E. F., … Foley, J. A. (2009). A safe operating space for humanity. *Nature*, *461*(7263), 472–475.

Scheffer, M., Carpenter, S., Foley, J. A., Folke, C., & Walker, B. (2001). Catastrophic shifts in ecosystems. *Nature*, *413*(6856), 591–596.

Schlenker, W. & Roberts, M. J. (2006). Nonlinear effects of weather on corn yields. *Review Of Agricultural Economics*, *28*(3), 391–398.

Schlenker, W. & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to u.s. crop yields under climate change. *Proceedings Of The National Academy Of Sciences*, *106*(37), 15594–15598.

Semenza, J. C., McCullough, J. E., Flanders, W. D., McGeehin, M. A., & Lumpkin, J. R. (1999). Excess hospital admissions during the july 1995 heat wave in chicago. *American Journal Of Preventive Medicine*, *16*(4), 269–277.

Semenza, J. C., Rubin, C. H., Falter, K. H., Selanikio, J. D., Flanders, D., Howe, H. L., & Wilhelm, J. L. (1996). Heat-related deaths during the july 1995 heat wave in chicago. *The New England Journal of Medicine*, *335*(2), 84–90.

Seneviratne, S. I., Lüthi, D., Litschi, M., & Schär, C. (2006). Land–atmosphere coupling and climate change in europe. *Nature*, *443*(14), 205–209.

Smith, K. R. & Haigler, E. (2008). Co-benefits of climate mitigation and health protection in energy systems: scoping methods. *Annual Review Of Public Health*, *29*, 11–25.

Smith, T. T., Zaitchik, B. F., & Gohlke, J. M. (2013). Heat waves in the united states: definitions, patterns and trends. *Climatic Change*, *118*(3), 811–825.

Snyder, R. L. (1985). Hand calculating degree days. *Agricultural and Forest Meteorology*, *35*(1), 353–358.

Stern, N. H. (2006). *Stern review: the economics of climate change*. London: HM Treasury.

Stuckler, D., Basu, S., Suhrcke, M., Coutts, A., & McKee, M. (2009). The public health effect of economic crises and alternative policy responses in europe: an empirical analysis. *Lancet*, *374*(9686), 315–323.

Thrasher, B., Maurer, E. P., McKellar, C., & Duffy, P. B. (2012). Technical note: bias correcting climate model simulated daily temperature extremes with quantile mapping. *Hydrology and Earth System Sciences*, *16*(9), 3309–3314.

Tol, R. S. J. (2005). The marginal damage costs of carbon dioxide emissions: an assessment of uncertainties. *Energy Policy*, *33*(16), 2064–2074.

United Nations, Department of Economics. (2015). *World population prospects*. Retrieved from https://esa.un.org/unpd/wpp/

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., ... Rose, S. K. (2011). The representative concentration pathways: an overview. *Climatic Change*, *109*(1), 5–31.

Vandentorren, S., Bretin, P., Zeghnoun, A., Mandereau-Bruno, L., Croisier, A., Cochet, C., ... Ledrans, M. (2006). August 2003 heat wave in france: risk factors for death of elderly people living at home. *European Journal Of Public Health*, *16*(6), 583–591.

Vandentorren, S., Suzan, F., Medina, S., Pascal, M., Maulpoix, A., Cohen, J.-C., & Ledrans, M. (2004). Mortality in 13 french cities during the august 2003 heat wave. *American Journal Of Public Health*, *94*(9), 1518–1520.

Vautard, R., Yiou, P., & Ghil, M. (1992). Singular-spectrum analysis: a toolkit for short, noisy, chaotic signals. *Physica D: Nonlinear Phenomena*, *58*(1), 95–126.

Watts, N., Adger, W. N., Agnolucci, P., Blackstock, J., Byass, P., Cai, W., ... Costello, A. (2015). Health and climate change: policy responses to protect public health. *The Lancet*, *386*(10006), 1861–1914.

Weisskopf, M. G., Anderson, H. A., Foldy, S., Hanahan, L. P., Blair, K., & Török, T. J. (2002). Heat wave morbidity and mortality, milwaukee, wis, 1999 vs 1995: an improved response? *American Journal Of Public Health*, *92*(5), 830–833.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review Of Economics And Statistics*, *91*(1), 1–19.

Weitzman, M. L. (2011). Fat-tailed uncertainty in the economics of catastrophic climate change. *Review of Environmental Economics and Policy*, *5*(2), 275–292.

Whitman, S., Good, G., Donoghue, E. R., Benbow, N., Shou, W., & Mou, S. (1997). Mortality in chicago attributed to the july 1995 heat wave. *American Journal Of Public Health*, *87*(9), 1515–1518.

Younger, M., Morrow-Almeida, H. R., Vindigni, M., Stephen, & Dannenberg, A. L. (2008). The built environment, climate change, and health: opportunities for co-benefits. *American Journal Of Preventive Medicine*, *35*(5), 517–526.

Zanobetti, A., O'Neill, M. S., Gronlund, C. J., & Schwartz, J. D. (2013). Susceptibility to mortality in weather extremes: effect modification by personal and small-area characteristics. *Epidemiology*, *24*(6), 809–819.

Appendix

Tables

country	excess deaths from June to September 2003 (singular systems analysis)	(Robine et al., 2008)
Belgium	437	1,175
France	16,247	19,490
Germany	7,811	9,355
Italy	25,387	20,089
Netherlands	519	965
Portugal	3,009	2,696
Slovenia	245	289
Spain	12,159	15,090
Switzerland	965	1,039
total	66,779	70,188

Table A-1: **Heat-caused country-by-country excess mortality during Summer 2003 in Europe.** The approach using singular systems analysis is the described in depth in the main body of the first chapter; Robine et al. (2008) use hospital-level data.

country	data length (years)	-3σ		-2σ		+2σ		+3σ	
Austria	54	0.03		0.01	*	0.01	***	-0.10	
Belgium	39	0.00		0.01	***	0.01	***	0.01	
Bulgaria	20	0.14		0.05	***	0.01	***	0.01	
Croatia	22	-0.59	**	0.04	**	0.01	***	-0.06	
Czech Republic	19	-0.11		0.00		0.01	***	- 0.06	
Denmark	54	0.04		0.00		0.01	***	0.03	
Estonia	39	-0.26	**	0.08	***	0.04	***	-0.04	
Finland	54	0.01	**	0.00		0.02	***	-2.02	
France	19	0.15	**	0.02	***	0.01	***	0.04	***
Germany	23	0.01		0.01		0.01	***	0.04	
Greece	54	0.00		0.02	***	0.07	***	-0.09	
Hungary	20			0.01		0.01	***	0.11	*
Italy	54	-0.05		0.03	***	0.03	***	-0.35	
Latvia	18	0.04	*	0.01		0.01	***		
Lithuania	20	0.01		0.01	**	0.01	***	-0.45	
Macedonia	19	-2.42		0.02	**	0.01	***	-0.03	
Netherlands	24	0.04		0.01	**	0.01	***	0.01	
Norway	54	0.00		0.01	***	0.01	***	-0.06	
Poland	19	-0.01		0.01	**	0.01	***	0.37	
Portugal	54	-0.22		0.09	***	0.02	***	0.10	***
Romania	19	-0.43		0.03	**	0.01	**	-0.02	
Slovakia	18	0.05		0.01		0.01	***	0.00	
Slovenia	18	-0.23		0.01		0.01	***	-0.02	
Spain	39	-0.26	**	0.08	***	0.04	***	-0.04	
Sweden	54	0.01		0.01	**	0.01	***	0.01	
Switzerland	54	0.00		0.01	*	0.01	***	0.00	
United Kingdom	32	0.01		0.01		0.01	***	-0.01	

*** p<0.01, ** p<0.05, * p<0.1

Table A-2: **Regression coefficients of extreme temperature measures.** Regression coefficients represent the increase in monthly mortality rates for each extreme temperature event.

country	excess mortality (% of total mortality)			
	(RCP 4.5)		(RCP 8.5)	
Austria	0.63	(± 0.52)	2.59	(± 0.99)
Belgium	-0.02	(± 0.34)	1.08	(± 0.78)
Bulgaria	0.29	(± 0.93)	2.71	(± 1.55)
Croatia	0.59	(± 0.55)	2.52	(± 1.02)
Czech Republic	0.31	(± 0.36)	1.48	(± 0.65)
Denmark	0.27	(± 0.30)	1.07	(± 0.75)
Estonia	0.02	(± 0.21)	0.74	(± 0.68)
Finland	0.22	(± 0.49)	1.73	(± 1.70)
France	-0.30	(± 0.83)	4.53	(± 3.78)
Germany	0.25	(± 0.37)	1.61	(± 0.80)
Greece	3.75	(± 3.37)	15.86	(± 7.78)
Hungary	0.64	(± 0.40)	1.92	(± 0.68)
Italy	1.81	(± 1.52)	7.78	(± 3.38)
Latvia	0.22	(± 0.24)	1.15	(± 0.78)
Lithuania	0.04	(± 0.36)	1.36	(± 1.00)
Macedonia	0.81	(± 0.84)	2.77	(± 1.16)
Netherlands	-0.28	(± 0.31)	1.01	(± 0.98)
Norway	-0.28	(± 0.37)	0.60	(± 0.92)
Poland	0.10	(± 0.39)	1.37	(± 0.79)
Portugal	-1.01	(± 0.38)	2.44	(± 3.26)
Romania	0.01	(± 0.41)	1.23	(± 0.68)
Slovakia	0.50	(± 0.42)	1.82	(± 0.71)
Slovenia	0.60	(± 0.34)	1.83	(± 0.64)
Spain	2.63	(± 2.47)	11.28	(± 5.29)
Sweden	-0.16	(± 0.25)	0.79	(± 0.91)
Switzerland	0.39	(± 0.40)	1.90	(± 0.77)
United Kingdom	0.24	(± 0.32)	1.30	(± 0.85)

Table A-3: **Estimated future climate change-caused excess mortality in Europe in 2091 – 2100.** Additional excess mortality is expressed in % of the forecasted national mortality rates. It is calculated for the decade of 2091 – 2100 as compared to the 1951 – 1980 baseline climatology assuming either moderate warming under RCP 4.5 or severe warming under RCP 8.5.

country	akaike information criterion	
	(singular systems analysis)	(fixed effects model)
Austria	-1,875	-770
Belgium	-1,250	-916
Bulgaria	-576	-605
Croatia	-819	-749
Czech Republic	-742	-702
Denmark	-2,078	-1,500
Estonia	-870	-576
Finland	-2,198	-2,219
France	-887	-872
Germany	-975	-892
Greece	-1,926	-1,505
Hungary	-653	-638
Italy	-1,785	-1,858
Latvia	-592	-608
Lithuania	-704	-436
Macedonia	-774	-652
Netherlands	-1,071	-1,071
Norway	-2,125	-1,642
Poland	-788	-812
Portugal	-1,547	-1,469
Romania	-596	-637
Slovakia	-796	-861
Slovenia	-707	-715
Spain	-1,552	-1,437
Sweden	-2,116	-1,911
Switzerland	-2,221	-1,801
United Kingdom	-1,038	-684

Table A-4: **Performance comparison of two different identification strategies using akaike information criterion.** The approach using singular systems analysis is the described in depth in the main body of chapter 1; the fixed effects model uses year- and month-fixed effects.

country	bayes information criterion	
	(singular systems analysis)	(fixed effects model)
Austria	-1,848	-694
Belgium	-1,225	-846
Bulgaria	-556	-546
Croatia	-797	-688
Czech Republic	-721	-644
Denmark	-2,051	-1,424
Estonia	-852	-517
Finland	-2,171	-2,143
France	-866	-814
Germany	-953	-830
Greece	-1,899	-1,429
Hungary	-636	-583
Italy	-1,758	1,782
Latvia	-575	-554
Lithuania	-683	-377
Macedonia	-753	-594
Netherlands	-1,049	-1,009
Norway	-2,098	-1,566
Poland	-768	-754
Portugal	-1,520	-1,393
Romania	-575	-579
Slovakia	-775	-803
Slovenia	-687	-658
Spain	-1,527	-1,402
Sweden	-2,089	-1,835
Switzerland	-2,194	-1,725
United Kingdom	-1,014	-617

Table A-5: **Performance comparison of two different identification strategies using bayes information criterion.** The approach using singular systems analysis is the described in depth in the main body of chapter 1; the fixed effects model uses year- and month-fixed effects.

country	leave-one-out cross validation (root mean squared error) (singular systems analysis)	 (fixed effects model)
Austria	0.06	0.13
Belgium	0.06	0.09
Bulgaria	0.07	0.07
Croatia	0.05	0.06
Czech Republic	0.05	0.05
Denmark	0.05	0.08
Estonia	0.06	0.09
Finland	0.07	0.07
France	0.08	0.05
Germany	0.04	0.05
Greece	0.06	0.08
Hungary	0.07	0.07
Italy	0.06	0.06
Latvia	0.06	0.06
Lithuania	0.06	0.10
Macedonia	0.04	0.06
Netherlands	0.04	0.04
Norway	0.05	0.07
Poland	0.06	0.05
Portugal	0.07	0.08
Romania	0.07	0.06
Slovakia	0.04	0.03
Slovenia	0.05	0.05
Spain	0.05	0.05
Sweden	0.05	0.06
Switzerland	0.04	0.06
United Kingdom	0.06	0.10

Table A-6: **Performance comparison of two different identification strategies using leave-one-out cross validation.** The approach using singular systems analysis is the described in depth in the main body of chapter 1; the fixed effects model uses year- and month-fixed effects.

Option A		Option B	
1/10 of \$2.00	9/10 of \$1.60	1/10 of \$3.85	9/10 of \$0.10
2/10 of \$2.00	8/10 of \$1.60	2/10 of \$3.85	8/10 of \$0.10
3/10 of \$2.00	7/10 of \$1.60	3/10 of \$3.85	7/10 of \$0.10
4/10 of \$2.00	6/10 of \$1.60	4/10 of \$3.85	6/10 of \$0.10
5/10 of \$2.00	5/10 of \$1.60	5/10 of \$3.85	5/10 of \$0.10
6/10 of \$2.00	4/10 of \$1.60	6/10 of \$3.85	4/10 of \$0.10
7/10 of \$2.00	3/10 of \$1.60	7/10 of \$3.85	3/10 of \$0.10
8/10 of \$2.00	2/10 of \$1.60	8/10 of \$3.85	2/10 of \$0.10
9/10 of \$2.00	1/10 of \$1.60	9/10 of \$3.85	1/10 of \$0.10
10/10 of \$2.00	0/10 of \$1.60	10/10 of \$3.85	0/10 of \$0.10

Table A-7: **Risk elicitation via the multiple price list method (Holt and Laury, 2002).** Participants of the laboratory experiment were asked to indicate whether they prefer option A or option B in each of the ten lotteries. A rational participant is expected to choose option B in the tenth lottery. In the first lottery, everyone but the most risk loving participants should choose option A. The level of risk aversion is determined by the lottery for which an individual switches from choosing option A to option B. The higher the risk aversion, the later this switch.

Were you generally satisfied with the outcome of the first game?
Very much — Somewhat — Not at all — I prefer not to tell

Were you generally satisfied with the outcome of the second game?
Very much — Somewhat — Not at all — I prefer not to tell

Was there anything that made you play differently in the second game than in the first? Why?
Yes — No — Unsure — Prefer not to tell / [Open question]

If you could choose which game to play, would you choose the first or the second? Why?
First — Second — Unsure — Prefer not to tell / [Open question]

Did fairness play a role for your contribution decision?
Very much — Somewhat — Not at all — I prefer not to tell

Did your willingness to take risks play a role for your contribution decision?
Very much — Somewhat — Not at all — I prefer not to tell

What was the most important reason for your contribution?
[Open question]

In what year were you born?
[Open question]

What is your gender?
Female — Male — Other — I prefer not to tell

What is your marital status?
Married — Widowed — Divorced — Separated — Never married — I prefer not to tell

Do you have any children?
Yes — No — I prefer not to tell

What is/was your major?
[Open question]

Do you have any final comments on your experience?
[Open question]

Table A-8: **Questionnaire for laboratory experiment.** Participants of the laboratory experiment were asked to answer the questions, but were not required to do so.