Planning for the Future in the Face of Climate Change Uncertainty: Three Econometric Techniques Applied to the Challenges Facing Energy, Water, and Recreation Demand

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ABSTRACT

This dissertation consists of three separate research papers. Each paper uses a different econometric technique to analyze a problem relating to the social aspects of climate change. The first paper investigates a potential adaptive strategy to counteract warming stream waters through stream intervention projects. Using novel non-parametric matching estimation techniques it is shown that these intervention projects have positive effects on homeowners that are near to the stream but downstream of the project site. The second paper uses Bayesian econometric techniques to analyze survey data regarding the welfare losses experienced as a result of power outages across Europe. This paper shows how the severity and spatial distribution of these welfare losses will change as the climate warms, which enables the current electricity grid expansion taking place in Europe to account for these effects of climate change. The third paper uses Classical econometric techniques to estimate the effect of temperature on visitor recreation choices around Lake Tahoe. It is then shown that under climate scenarios the demand for beach and water access at Lake Tahoe will greatly increase, which suggests that lake managers begin to plan regulations and build infrastructure to account for this demand increase.

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Introduction

This dissertation presents three separate research projects in the fields of energy, and environmental economics. The three works are linked by the common goal of understanding, and planning for the future energy and environmental needs of society under the uncertain conditions of climate change. Since climate change will affect nearly every aspect of modern society, analysis of climate change issues can require varied econometric techniques to account for different data structures. This dissertation illustrates three distinct applied econometric techniques and their applications to climate change economics: Chapter 1 develops and uses matching estimators, Chapter 2 uses a hierarchical Bayesian model for data analysis, while Chapter 3 uses well-developed Classical techniques.

Chapter 1 develops a conceptual framework which addresses unobserved spatial and temporal effects in hedonic matching estimation. We explore three strategies of controlling for these effects including a 2-Stage Bias Corrected Matching Estimator (2SBCME). This flexible estimation technique can be used to control for unobserved heterogeneity from a variety of sources, including cases where existing methods are not feasible. We illustrate these methods with a valuation study of the effects of stream intervention projects on home prices for homes located downstream from the project site. Past research has shown that homeowners who live nearby stream restoration projects experience a welfare increase from these projects. However, this may only be part of the realized benefit, since homeowners downstream of the project may also experience welfare increases. We estimate the effect on welfare to downstream homeowners using matching methods and home sales data from the area near Johnson Creek in Portland, Oregon. Our results indicate that the projects investigated increased downstream home values by 6-10%. For related literature this suggests that focusing on adjacency effects alone will lead to downward bias in the overall welfare estimates from riparian interventions. For social planners this suggests that stream intervention projects of the type studied in this chapter have positive effects on stream quality which are perceived by nearby residents. As climate change is likely to lead to a general degradation in urban stream quality by warming the water, stream interventions offer a possible adaptation to this change that will improve the welfare of homeowners near to the stream.

Chapter 2 investigates the relationship between temperature and the economic losses from power outages. Electricity blackouts exact a large cost on society. A substantial part of this cost is the welfare loss experienced by households. Electricity consumption has been shown to vary with temperature as climate control is a large proportion of household electricity use. Data from a choice experiment designed to elicit willingness to pay (WTP) to avoid power outages is linked to respondent-specific temperature measures from a sample of 19 EU nations. These data are used to estimate a Bayesian hierarchical model where coefficients are allowed to vary by the season in which the hypothetical outage takes place. This exercise yields estimates of WTP to avoid an hour of power outage between €0.38 - €2.05 per household, which varies based on the season and scope of the outage, with winter outages currently incurring larger per household hourly welfare losses than summer outages. The results also show that temperature is a strong driver of WTP, where increases in summer temperatures increase WTP, while increases in winter temperatures decrease WTP. The estimated marginal effects of temperature on WTP are used to impute WTP across space, and into the future based on temperature predictions from the Hadley CM3 climate model. These imputations show that, under plausible future climates, the cost of power outages to households will increase on average. This information will allow the European Union to optimize its' current effort to overhaul the electricity grid to account for long term changes to the severity and spatial distribution of welfare losses from blackouts.

Chapter 3 presents research regarding the relationship between temperature and visitor recreation choices at Lake Tahoe. The estimated effect of temperature on such choices is used to predict the proportion of visitor man-hours that will be spent on different types of activities under global warming scenarios. The diary data used account for the activity choices of all household members for each hour of the day on the day of the survey. These data are analyzed using hierarchical mixed models with a combination of random effects at the household level and fixed or random effects at the survey site level. The results show that warmer temperatures lead to a larger share of visitors' time being allocated to water and beach activities while less time is spent at indoor leisure and at their accommodation. Combining these results with an estimate of the overall visitation trend to Lake Tahoe, we estimate that demand will increase by 130-160% for beach activities, and by 115-133%

for water use. Since the high volume of Tahoe beach and water users already stresses the Lake's ecosystem and the current infrastructure, the results of this study underscore the need for further infrastructure and regulations to be developed that can account for the future increase in demand for beach and water access.

Chapter 1

Matching estimation with confounding factors: Estimating the effect of stream improvements on downstream home values

1.1 Introduction

Non-parametric matching estimators offer a flexible alternative to traditional hedonic models for estimating treatment effects in non-market valuation studies. The traditional method relies on the parametric estimation of a full hedonic price function [65]. However misspecification of this price function can cause the estimated treatment effect to be misleading [43]. Matching avoids explicit specification of the hedonic price function, but is still subject to omitted variable problems if unobserved factors are correlated with the treatment effect of interest, thus violating the "conditional independence" assumption of matching [72]. The conditional independence assumption is unlikely to hold in cases where the sample comprise spatially diverse subsets of individuals, such as homes from different neighborhoods. While a variety of matching methods for dealing with observed variables are well-documented [31, 72], such as propensity score, nearest neighbor, or exact matching, methods of controlling for unobserved spatial and temporal factors in matching have yet to be fully explored. To date, Abbott and Klaiber [3] have the only paper which deals with unobserved factors in a matching estimation. The authors explore the tradeoff between forcing matching to be within a homogenous spatial zone, to control for unobserved spatial factors, versus matching outside of the spatial zone to improve match quality based on observed housing characteristics. We add to the emerging hedonic matching literature by showing three methods of controlling for unobserved spatial heterogeneity in matching estimators, and illustrating these methods with a conceptual framework and an empirical application.

The first method is to force both treated and control homes to be within the same spatial/temporal unit, where both are subject to the same unobserved effects, thus eliminating these confounding factors. However, when the sample of control homes within a given zone is small, this solution can lead to significant matching bias from poor balance on observable home characteristics. The second method affords better post-matching balance in small samples by allowing for matching across zones and controlling for unobserved effects through fixed effect terms in the auxiliary bias-adjustment regression [2]. However, if some zones contain only treated homes, but no controls, then neither of the first two methods can be applied, as is the case for one of the stream interventions we investigate. This leads to the development of the third method of controlling for unobserved heterogeneity, the 2-stage Bias Corrected Matching Estimator (2SBCME). This method uses a separate first stage matching estimation to estimate confounding effects which are then differenced out from the second stage treatment effect.

These three methods are illustrated in an application to two stream improvement projects which took place along Johnson Creek in Portland, Oregon. Previous research into the effect of changing riparian conditions on home values, often as a result of interventions, has focused on homes near to the project site [e.g. 71, 14, 60, 11]. Our application tests the possibility that positive benefits from improvement projects also matriculate downstream from the project site and increase home values far from the intervention itself. In the case of the two projects considered, we find evidence that downstream home values increased as a result of the projects, which suggests that future research should consider downstream benefits, in addition to adjacency benefits, to allow for a more complete valuation of the societal gains from riparian improvements.

1.2 Matching estimation with confounding factors

To date, the methodological contributions to the matching literature have assumed that the conditional independence assumption holds. We develop a simple conceptual framework with which we investigate the properties of the matching estimator when this assumption does not hold, namely in the presence of spatial and temporal confounding factors. We then illustrate three strategies of controlling for these confounding factors within the conceptual framework. As a starting point, we briefly explain our preferred matching estimation procedure which uses the Bias Corrected Matching Estimator (BCME) of Abadie and Imbens [2]. We frame our discussion with a matching estimation of the ATT (average treatment effect on the treated), since this is often the quantity most relevant in applied research, though the results are easily generalizable to other treatment effects.

1.2.1 Matching estimation

The first step of the matching procedure is a data processing method which attempts to 'balance' the treated and control samples on observed covariates. This is done by selecting from the sample of control homes so that the distributions of observed covariates are as similar as possible between the two sub-samples. To achieve optimal balance between the treated and control sub-samples we employ the Diamond and Sekhon [24] GenMatch algorithm for the first time in a hedonic matching context. The GenMatch optimization routine looks for the vector of weights that produces optimal balance, as measured by a variety of test statistics. The improved balance from using GenMatch helps make the treatment independent, or nearly, of observed variables. This greatly reduces the reliance on a correctly specified parametric model (as in traditional hedonic analysis) to control for differences in observables between groups [31]. The matching method we prefer is the nearest-neighbor method (with replacement, and keeping ties) as proposed in Abadie and Imbens [1]. This method searches for matches based on minimizing distance measure d_{ij}, which is the vector distance between treated observation i and control j.

$$d_{ij} = \sqrt{(\mathbf{x}_i - \mathbf{x}_j)' \mathbf{V}^{-1/2} \mathbf{W} \mathbf{V}^{-1/2} (\mathbf{x}_i - \mathbf{x}_j)} \tag{1.1}$$

Where $\mathbf{x}_i$ and $\mathbf{x}_j$ are corresponding vectors of observable variables and $\mathbf{V}$ is the variance-covariance matrix of these observables in the entire data. Matrix $\mathbf{W}$ is a diagonal matrix of weights which we estimate using the Diamond and Sekhon [24] GenMatch algorithm.

The next step in the procedure is to use the matched sample to calculate the ATT. Following Abadie and Imbens [1] and Abadie and Imbens [2] we can show the Bias Corrected Matching Estimator (BCME) for the ATT ($\hat{\tau}_{att}$) as:

$$\begin{aligned} \hat{y}_{0i} &= \tfrac{1}{n_i} \sum_{j \in \mathcal{J}_{i,n_i}} \left(y_{0j} + \hat{\mu}_0 \left(\mathbf{z}_i \right) - \hat{\mu}_0 \left(\mathbf{z}_j \right) \right) \\ \hat{\tau}_{att} &= \tfrac{1}{N} \sum_{i=1}^{N} \left(y_{1i} - \hat{y}_{0i} \right), \end{aligned} \tag{1.2}$$

where $\hat{y}_{0i}$ is the counterfactual price of treated home sale i if it had not received the treatment. This counterfactual price is computed as the average of the prices of all the matched control homes y_{0j}, where $\mathcal{J}_{i,n_i}$ is the set of all control homes matched to home i, given a number of matches n_i. The terms $\hat{\mu}_0 \left(\mathbf{z}_i \right)$ and $\hat{\mu}_0 \left(\mathbf{z}_j \right)$ are simple regression function predictions from an auxiliary regression, using only matched control observations, of the home prices of homes i and j, respectively, given observable home characteristics $\mathbf{z}_i$ and $\mathbf{z}_j$[1]. The ATT of home sale i is then just the difference between the counterfactual estimate and the observed home sale price. The estimated ATT for the sample of N treated homes is the average of these individual ATTs. The addition of predictions from an auxiliary regression reduces bias in the matching estimator that results from imperfect matches on observed variables in any treated-control home sale pair (see Abadie and Imbens [2] for more information on bias-adjustment). This renders the matching estimator consistent even under misspecification of the auxiliary regression function. However, this result was established under the assumption of conditional independence. In what follows we offer a conceptual investigation of the BCME when this assumption does not hold.

1.2.2 Conceptual framework with unobserved spatial and temporal effects

Let index i denote one treated observation (e.g. home sale) from the sample of treated, and index j control observations eligible for matching to estimate the primary treatment effect of interest. Furthermore, let k, f and m be additional groups of untreated homes that may

[1] Here we use $\mathbf{z}_i$ and $\mathbf{z}_j$ as opposed to $\mathbf{x}_i$ and $\mathbf{x}_j$ to allow other variables besides those used in the matching algorithm to enter the auxiliary regression, such as a fixed effect term.

or may not be eligible for matching, as discussed below in more detail. Correspondingly, let $\mathbf{x}_i$ be observed structural characteristics for i, $\mathbf{x}_j$ for j, and so on.

We will also allow for unobserved spatial effects α and temporal effects ν. These will be indexed according to the observation group (i, j, etc.). These effects vary based on the spatial and temporal unit in which the observation took place. Then y_{1i} is the observed sales price of the treated home, and y_{0i} is the unobserved counterfactual - what the home would have sold for in absence of treatment. Let the true population expectations - conditional on $\mathbf{x}_i$ - for both cases be given as:

$$\begin{aligned} E\left(y_{1i}|\mathbf{x}_i, \alpha_i, \nu_i\right) &= \mu_1\left(\mathbf{x}_i\right) + \alpha_i + \nu_i \\ E\left(y_{0i}|\mathbf{x}_i, \alpha_i, \nu_i\right) &= \mu_0\left(\mathbf{x}_i\right) + \alpha_i + \nu_i \end{aligned} \tag{1.3}$$

We allow the unobserved effects to be additively separable from the portion of the expectation that is uniquely defined by observed structural characteristics. Our goal in all the cases considered below is to estimate the true treatment effect for home i, which is given as:

$$T_i = \mu_1\left(\mathbf{x}_i\right) - \mu_0\left(\mathbf{x}_i\right) \tag{1.4}$$

Assuming single (or 1:1) nearest-neighbor matching for simplicity, the bias corrected estimate of the treatment effect based on a matched control observation j can then be written as:

$$\begin{aligned} \hat{T}_i &= y_{1i} - \hat{y}_{0i} \\ \hat{y}_{0i} &= y_{0j} + \hat{\mu}_0\left(\mathbf{x}_i\right) - \hat{\mu}_0\left(\mathbf{x}_j\right) \end{aligned} \tag{1.5}$$

where, as usual, $\hat{\mu}_0\left(.\right)$ are predicted outcomes for the treated and the control observations flowing from an auxiliary regression that is run using only *matched controls*. Then the expectation of the estimated treatment effect for home i would be

$$E\left(\hat{T}_i\right) = \mu_1\left(\mathbf{x}_i\right) + \alpha_i + \nu_i - \left[\mu_0\left(\mathbf{x}_j\right) + \alpha_j + \nu_j + \hat{\mu}_0\left(\mathbf{x}_i\right) - \hat{\mu}_0\left(\mathbf{x}_j\right)\right] \tag{1.6}$$

which, regardless of the quality of the match between i and j, would be biased by the quantity $(\alpha_i + \nu_i - \alpha_j - \nu_j)$. This implies that we need to purge our estimate $\hat{T}_i$ of the unobserved spatial and temporal effects. We examine three methods of doing so:

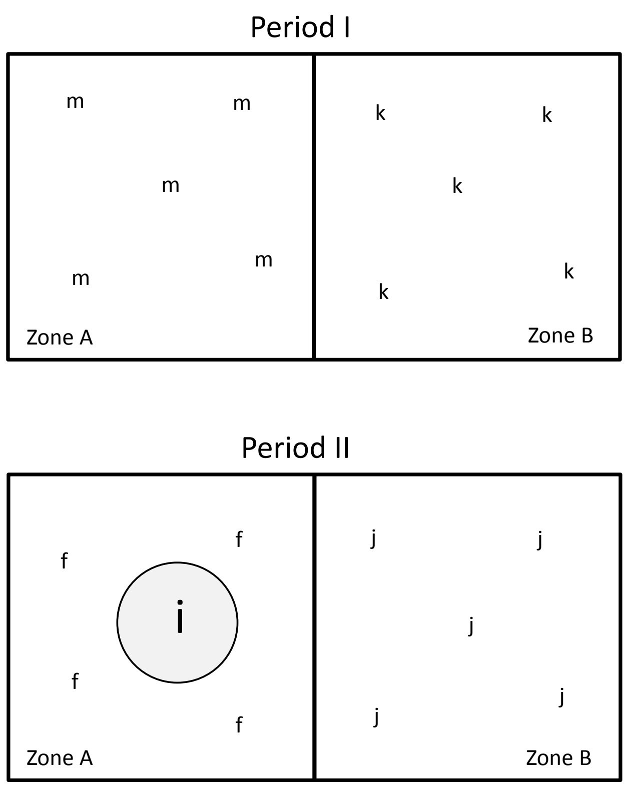
(a) Force the matched control observation to come from within the same spatial and/or temporal unit as the treated observation.

(b) Estimate spatial and/or temporal fixed effects within the auxiliary regression.

(c) Use the 2-Stage Bias Corrected Matching Estimator (2SBCME) presented below to eliminate spatial and/or temporal effects.

We illustrate and compare these three strategies for a singe treated observation i; for simplicity the conceptual scenario has two time periods and two spatial zones. Any given treated home out of the sample of treated will be within one particular spatial unit and one temporal unit. Without loss of generality we arbitrarily place our treated home i within spatial unit A and time period II, as shown in figure 1.1, and derive all results from this perspective. The results are generalizable for treated observations which come from any combination of temporal and spatial units by merely changing the relevant subscripts.

Figure 1.1: Conceptual Framework: treated observation i with f, j, m, and k candidate control observations



Initially we have eligible controls spread across all relevant spatial and temporal units, as illustrated in figure 1.1, and do not encounter controls that are ineligible for the matching estimation. Strategies (a), (b), and (c) above can all be employed. Focusing on strategies (a) and (b) for now, if i is matched to an f, either because the f home minimizes the distance measure shown in (1.1) or because we force a match to an f home under strategy (a), then $\alpha_i = \alpha_f$ and $\nu_i = \nu_f$, and the expectation of the estimated treatment effect simplifies to:

$$\begin{aligned}
&E\left(\hat{T}_i|\mathbf{x}_i, \{\mathbf{x}_f\}_{f=1}^F\right) = \\
&E\left(y_{1i}|\mathbf{x}_i, \alpha_i, \nu_i\right) - E\left(\hat{y}_{0i}|\mathbf{x}_i, \{\mathbf{x}_f\}_{f=1}^F, \alpha_f, \nu_f\right) = \\
&\mu_1\left(\mathbf{x}_i\right) + \alpha_i + \nu_i - \left(\mu_0\left(\mathbf{x}_f\right) + \alpha_f + \nu_f\right) - \left[E\left(\hat{\mu}_0\left(\mathbf{x}_i\right)\right) - E\left(\hat{\mu}_0\left(\mathbf{x}_f\right)\right)\right] = \\
&\mu_1\left(\mathbf{x}_i\right) - \mu_0\left(\mathbf{x}_f\right) - \left[E\left(\hat{\mu}_0\left(\mathbf{x}_i\right)\right) - E\left(\hat{\mu}_0\left(\mathbf{x}_f\right)\right)\right]
\end{aligned} \tag{1.7}$$

This is the standard case of Abadie and Imbens [2] doubly-robust BCME, which produces an unbiased estimate of the true treatment effect if

1. $\mathbf{x}_i = \mathbf{x}_f$, OR
2. $\mathbf{x}_i \neq \mathbf{x}_f$, and $E\left(\hat{\mu}_0\left(\mathbf{x}_r\right)\right) = \mu_0\left(\mathbf{x}_r\right), r = i, f$.

Therefore, the closer the match based on observables, the less burden is placed on the auxiliary regression model to correct the remaining bias. An example of this case would be the matching estimation of Muehlenbachs et al. [53], who force matches to be within the same year and census tract. However, in many cases we would like to expand the spatial/temporal radius that holds eligible controls to get better matches based on the $\mathbf{x}_i$ variables, which would often mean allowing controls to be located in different spatial and/or temporal units than the treated home i. To control for unobserved factors in this case we could employ strategy (b). If i is matched to a j home and i and j are in different spatial zones then $\alpha_i \neq \alpha_j$, but they are in the same time period, so $\nu_i = \nu_j$. The expectation of the estimate is:

$$\begin{aligned}
&E\left(\hat{T}_i|\mathbf{x}_i, \{\mathbf{x}_j\}_{j=1}^J, \{\mathbf{x}_k\}_{k=1}^K, \{\mathbf{x}_m\}_{m=1}^M, \{\mathbf{x}_f\}_{f=1}^F, \alpha_i, \alpha_j\right) = \\
&E\left(y_{1i}|\mathbf{x}_i, \alpha_i\right) - E\left(\hat{y}_{0i}|\mathbf{x}_i, \{\mathbf{x}_j\}_{j=1}^J, \{\mathbf{x}_k\}_{k=1}^K, \{\mathbf{x}_m\}_{m=1}^M, \{\mathbf{x}_f\}_{f=1}^F, \alpha_j\right) = \\
&\left(\mu_1\left(\mathbf{x}_i\right) + \alpha_i\right) - \left(\mu_0\left(\mathbf{x}_j\right) + \alpha_j\right) - \left[E\left(\hat{\mu}_0\left(\mathbf{x}_i\right) + \hat{\alpha}_i\right) - E\left(\hat{\mu}_0\left(\mathbf{x}_j\right) + \hat{\alpha}_j\right)\right]
\end{aligned} \tag{1.8}$$

and the time effects cancel out. The $\hat{\alpha}$-terms are spatial fixed effects which are estimated in the auxiliary regression. If instead i is matched to an m home then $\nu_i \neq \nu_m$ and $\alpha_i = \alpha_m$, with the expectation of the estimate as

$$\begin{aligned}
&E\left(\hat{T}_i|\mathbf{x}_i,\{\mathbf{x}_j\}_{j=1}^J,\{\mathbf{x}_k\}_{k=1}^K,\{\mathbf{x}_m\}_{m=1}^M,\{\mathbf{x}_f\}_{f=1}^F,\nu_i,\nu_m\right)= \\
&E\left(y_{1i}|\mathbf{x}_i,\nu_i\right)-E\left(\hat{y}_{0i}|\mathbf{x}_i,\{\mathbf{x}_j\}_{j=1}^J,\{\mathbf{x}_k\}_{k=1}^K,\{\mathbf{x}_m\}_{m=1}^M,\{\mathbf{x}_f\}_{f=1}^F,\nu_m\right)= \\
&\left(\mu_1\left(\mathbf{x}_i\right)+\nu_i\right)-\left(\mu_0\left(\mathbf{x}_m\right)+\nu_m\right)-\left[E\left(\hat{\mu}_0\left(\mathbf{x}_i\right)+\hat{\nu}_i\right)-E\left(\hat{\mu}_0\left(\mathbf{x}_m\right)+\hat{\nu}_m\right)\right]
\end{aligned} \tag{1.9}$$

and the spatial effects cancel out. The $\hat{\nu}$-terms are temporal fixed effects which are estimated in the auxiliary regression. Finally, if the 'nearest' home to i is a k home then $\nu_i \neq \nu_k$ and $\alpha_i \neq \alpha_k$

$$\begin{aligned}
&E\left(\hat{T}_i|\mathbf{x}_i,\{\mathbf{x}_j\}_{j=1}^J,\{\mathbf{x}_k\}_{k=1}^K,\{\mathbf{x}_m\}_{m=1}^M,\{\mathbf{x}_f\}_{f=1}^F,\alpha_i,\alpha_k,\nu_i,\nu_k\right)= \\
&E\left(y_{1i}|\mathbf{x}_i,\alpha_i,\nu_i\right)-E\left(\hat{y}_{0i}|\mathbf{x}_i,\{\mathbf{x}_j\}_{j=1}^J,\{\mathbf{x}_k\}_{k=1}^K,\{\mathbf{x}_m\}_{m=1}^M,\{\mathbf{x}_f\}_{f=1}^F,\alpha_k,\nu_k\right)= \\
&\left(\mu_1\left(\mathbf{x}_i\right)+\alpha_i+\nu_i\right)-\left(\mu_0\left(\mathbf{x}_k\right)+\alpha_k+\nu_k\right)-\left[E\left(\hat{\mu}_0\left(\mathbf{x}_i\right)+\hat{\alpha}_i+\hat{\nu}_i\right)-E\left(\hat{\mu}_0\left(\mathbf{x}_k\right)+\hat{\alpha}_k+\hat{\nu}_k\right)\right]
\end{aligned} \tag{1.10}$$

Note that these expectations are conditioned on all matched $\mathbf{x}_j$, $\mathbf{x}_k$, $\mathbf{x}_m$ and $\mathbf{x}_f$ for the sample at large, as indicated by the notation above, where J, K, M and F denote the total number of matched j's and k's, etc., respectively. This is because the auxiliary regression uses all matched control observations in generating predicted prices and estimating the fixed effects. An unbiased estimate of the true treatment effect $T_i = \mu_1(\mathbf{x}_i) - \mu_0(\mathbf{x}_i)$ can be obtained under two circumstances:

1. $\mathbf{x}_i = \mathbf{x}_l$, and $E(\hat{\alpha}_r) = \alpha_r, E(\hat{\nu}_r) = \nu_r, \{r = i,j,k,m \quad l = j,k,m\}$ - that is, we have a perfect match based on observable home characteristics, and the included spatial and/or temporal fixed effects are estimated without bias, OR

2. $\mathbf{x}_i \neq \mathbf{x}_l$, and $E(\hat{\mu}_0(\mathbf{x}_r)) = \mu_0(\mathbf{x}_r), \{r = i,j,k,m \quad l = j,k,m\}$ - in addition to the unbiased estimation of spatial and temporal effects. That is, we have an imperfect match, but the auxiliary regression produces unbiased predictions of home prices for both observations.

Again, from an estimation perspective, strategy (b) is only feasible if the *matched* control observations are spread over all relevant spatial and temporal units, such that the unobserved effects can be estimated in the auxiliary regression. This may not always hold in a given application. However, when strategy (b) is not possible the 2SBCME can often be used instead, as explained below.

1.2.3 2-Stage Bias Corrected Matching Estimator

The 2SBCME often becomes necessary in cases where many of the potential control observations are ineligible for matching estimation to derive the primary ATT of interest. For this example assume that only the j group of controls in figure 1.1 is eligible for matching and that all other groups of controls besides the j group are *ineligible*. A control observation would be ineligible if the researcher determines that using it in the matching estimator would not estimate the treatment effect of interest, or would possibly introduce other confounding effects into the estimation.

Facing a large sample of ineligible controls is likely to be the norm in hedonic matching estimations. For example, in our application we consider only homes that are within 250m of the waterway to be eligible and all others to be ineligible. We then encounter a situation which mirrors this conceptual case where all eligible controls are located in different spatial units (unified school district zones) than our treated homes but many ineligible home sale observations are available in all spatial units. In these cases our *only* option for controlling for spatial confounding effects is to employ the 2SBCME approach since we will not have matched control homes in the same zone as the treated with which to estimate the spatial fixed effects in the auxiliary regression, as required by strategy (b). In cases where strategy (b) is feasible, the 2SBCME can still be used and may be preferred to alleviate the burden on the auxiliary regression if, for example, this regression is estimated with a small sample of unique control observations.

In step one we match controls from zone A (f), against controls from zone B (m), to estimate the pure spatial price effect, using controls that would be ineligible to estimate the ATT of primary interest. Then, in step two, we match the treated home i to its closest match j home (an eligible control), and subtract the spatial effect. To make the 2SBCME operational we need a sample of controls in both time zones and ideally in the same time period to alleviate the risk of temporal confounding factors in the first stage estimation. We have:

$$\begin{aligned} &\nu_i = \nu_j = \nu_f, \forall j, f \\ &\alpha_i = \alpha_f = \alpha_A, \forall f \\ &\alpha_j = \alpha_B, \forall j \end{aligned} \tag{1.11}$$

The regression-adjusted first-stage estimator, matches f homes to j homes, from figure 1.1, to obtain an estimate of $\hat{T}_{A,B}$ which can be written as:

$$\begin{aligned} &\hat{T}_{A,B} = y_{0f} - \hat{y}_{0f}, \quad \text{with} \\ &\hat{y}_{0f} = y_{0j} + \hat{\mu}_0(\mathbf{x}_f) - \hat{\mu}_0(\mathbf{x}_j) \end{aligned} \tag{1.12}$$

It has the following expected value:

$$\begin{aligned} &E\left(\hat{T}_{A,B} | \{\mathbf{x}_j\}_{j=1}^J, \mathbf{x}_f\right) = \\ &(\mu_0(\mathbf{x}_f) + \alpha_A) - (\mu_0(\mathbf{x}_j) + \alpha_B) - \left[E(\hat{\mu}_0(\mathbf{x}_f)) - E(\hat{\mu}_0(\mathbf{x}_j))\right], \end{aligned} \tag{1.13}$$

which, as with the standard case of the BCME, will produce the desired spatial effect $\hat{T}_{A,B} = \alpha_A - \alpha_B$ for a perfect match, or an unbiased estimation of $\mu_0(\mathbf{x}_r), r = f, j$ from the auxiliary regression model. Step two then matches the original i against j, subtracting the spatial effect:

$$\begin{aligned} &\hat{T}_i = y_{1i} - \hat{y}_{0i} - \hat{T}_{A,B}, \quad \text{with} \\ &\hat{y}_{0i} = y_{0j} + \hat{\mu}_0(\mathbf{x}_i) - \hat{\mu}_0(\mathbf{x}_j), \end{aligned} \tag{1.14}$$

with expected value

$$\begin{aligned} &E\left(\hat{T}_i | \mathbf{x}_i, \{\mathbf{x}_j\}_{j=1}^J, \hat{T}_{A,B}\right) = \\ &(\mu_1(\mathbf{x}_i) + \alpha_A) - (\mu_0(\mathbf{x}_j) + \alpha_B) - (E(\hat{\mu}_0(\mathbf{x}_i)) - E(\hat{\mu}_0(\mathbf{x}_j))) - (\alpha_A - \alpha_B) = \\ &\mu_1(\mathbf{x}_i) - \mu_0(\mathbf{x}_j) - (E(\hat{\mu}_0(\mathbf{x}_i)) - E(\hat{\mu}_0(\mathbf{x}_j))) \end{aligned} \tag{1.15}$$

Thus, we purged the model of the confounding spatial effect, and are back to the basic setup for the BCME.

1.3 Application

We illustrate the three methods of controlling for unobserved spatial factors in a non-market valuation study of the effects of stream intervention projects on home values for homes downstream of the project site. This application is an ideal case study for our methodological consideration since the treatment, being downstream as opposed to upstream of a given intervention project, is spatially defined and thus is likely to be correlated with other spatial factors that affect home price. We delineate spatial groups of homes by Unified School District (UNSD) zones, since school quality has been shown to directly capitalize into home values [12, 21].[2] Temporal units are defined by the year in which the home sold.

Over the past decades more than a billion dollars annually has been invested in waterway and riparian area improvement projects across the nation [8]. A substantial portion of this investment is concentrated in the Pacific Northwest [40, 38]. A primary benefit of waterway improvement projects, aside from the larger goal of preserving freshwater resources, is the increased amenity value of the waterway experienced by nearby residents. Past studies have shown that various water quality measures and riparian ecosystem conditions have an effect on nearby homeowners which capitalizes into home price [e.g. 51, 48, 16, 58, 54, 71, 14, 60, 11]. These studies suggest that river, stream and riparian area improvement efforts have a generally positive effect on nearby home prices. Lewis et al. [50] investigate the marginal property price effect of moving further from a dam site, both before and after removal of the dam. The authors find that after removal of the dam, the home price discount of being near to the dam shrinks considerably. However, Lewis et al. [50] and other previous research have not explicitly considered the effect of waterway improvements on homes that are *downstream* of the improvement site. It is probable that positive benefits from the project matriculate down the stream with the flow of the water, improving the stream's amenity value to homeowners far from the project site. This research fills this gap by investigating the effect of large-scale stream intervention projects on home values for homes situated near to the waterway and downstream from the project site. If these homes do increase in value as a result of riparian improvement projects, then previous estimates of the benefits of such projects can only be interpreted as lower bounds on their true housing market impacts.

We estimate the effect on downstream home values from two large-scale intervention projects

[2] Finer scale spatial groupings may be preferable for eliminating spatial effects, however this would also exacerbate our small sample problems.

along Johnson Creek in Portland, Oregon. We hypothesize that homes which are downstream of these major intervention projects will experience increased amenity value and lower flood risk from the creek which will capitalize into home values. A variety of project outcomes can lead to increased amenity values from Johnson Creek for nearby homeowners. Foremost among them are: improved water quality and reduced odor, improved viewshed, increases in desirable wildlife, improved recreation opportunities (primarily walking and biking), and decreases in actual or perceived flood risk.

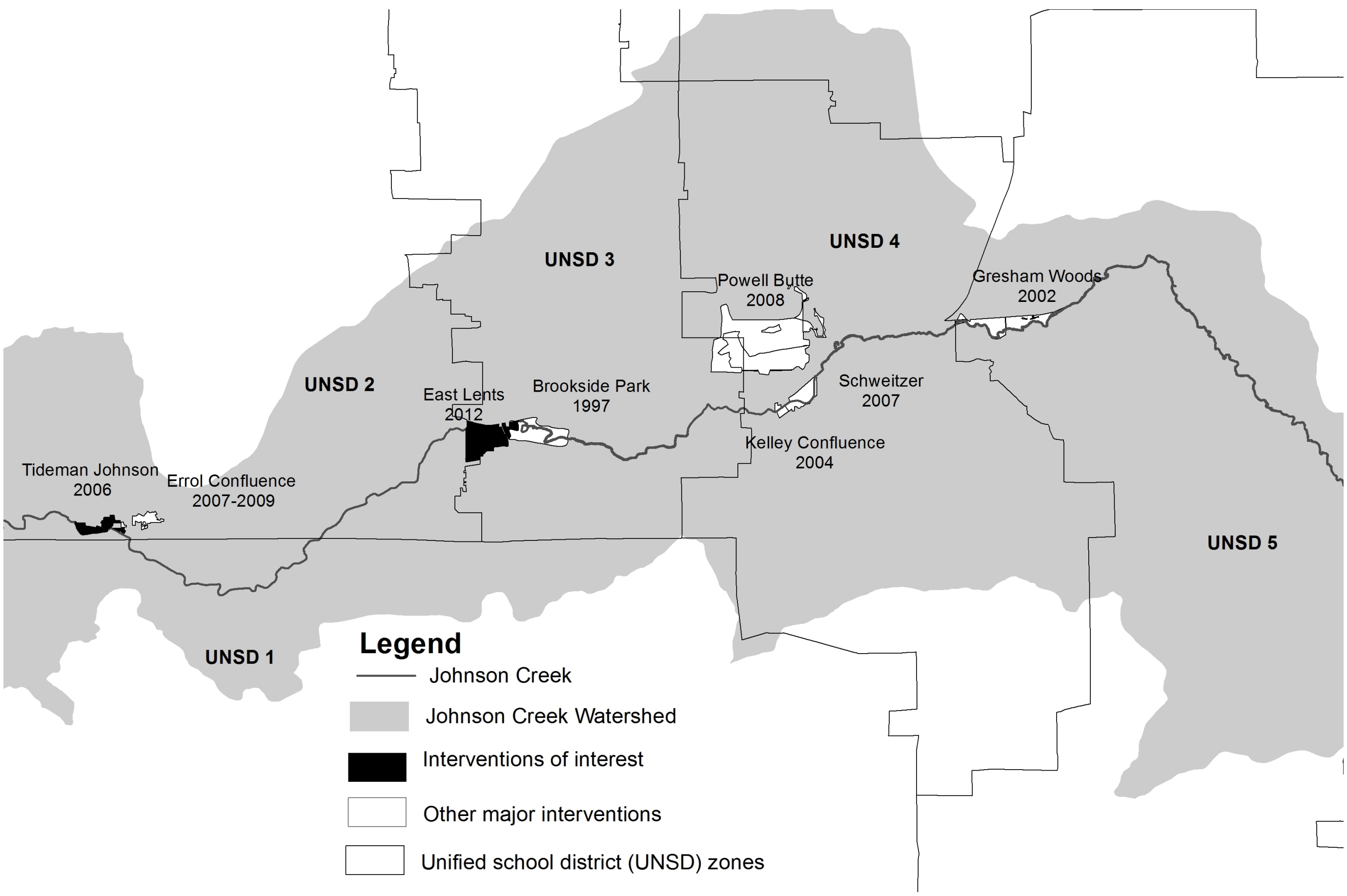
Braden and Johnston [14] give a synthesis of research regarding water quality effects on home values. The results of their synthesis show that, when taken together, improved water quality and reduced flood risk can amount to up to a 20% increase in home values. However, the studies surveyed give highly heterogeneous results based on methodology, the water system involved, and the interaction between the waterway and homeowners. Many of the homes we use in our study are near the 100 year floodplain, or are near to roads that are at risk of flooding. These homes may therefore be subject to considerable flood risk, making decreases in perceived flood risk as a result of stream improvements highly relevant for homeowners. Thus, we would expect to see positive and possibly substantial gains in downstream home values as a result of the large-scale projects along Johnson Creek.

1.3.1 Study Area

The study area for this project is the Johnson Creek Watershed in Portland, Oregon. Several large-scale intervention projects have taken place along the creek since 1997. We compared information from these projects and chose to focus our study on two of the larger, more-intensive projects along Johnson Creek, the Tideman-Johnson project, which took place in 2006, and the East Lents (a.k.a. Foster Floodplain) Project, which took place in 2012. An overview of Johnson Creek, the restoration projects of interest, and the relevant UNSD zones is given in figure 1.2.

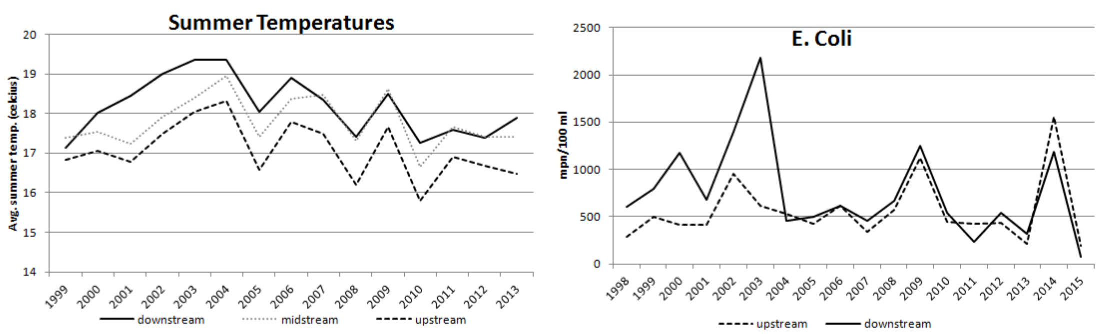
Johnson Creek runs through the southern side of Portland, eventually spilling into the Willamette river. The creek begins in the rural foothills to the southeast of Portland and runs 40 km westward. Along its route the creek is fed by seven tributaries, as well as a number of smaller flows. Due to the hydrology and geography of the Johnson Creek Watershed, the creek has a history of flooding, which puts nearby homeowners at risk. The creek also suffered from poor water quality and the degradation of wildlife habitat as a result of the development of the surrounding area. For these reasons, the Portland BES created the Johnson Creek Restoration Plan in 2001, which set out to improve the stream in a variety of ways [22]. The major stream improvement projects that have been completed along Johnson Creek are shown in figure 1.2. One major goal of the Restoration Plan is to decrease summer water temperatures in Johnson Creek to promote the health of the riparian ecosystem. Along with decreasing temperature, these stream intervention projects generally attempted to improve water quality, wildlife habitat, and flood storage of the Johnson Creek. [5]. As climate change is expected to bring warmer temperatures to the planet, warming streams may become a global issue. Stream interventions of the sort investigated herein represent an *adaptive* strategy which could possibly offset some of the freshwater warming caused by climate change.

Figure 1.2: Major intervention projects in the Johnson Creek Watershed



As a scientific indication of stream improvement due to intervention projects we look at water quality indicators over the study period (1990-2014). A reduction in summer water temperatures was specifically targeted in the Johnson Creek Restoration Plan [22]. Figure 1.3 shows the summer (June-Aug.) average temperatures for three monitoring stations along Johnson Creek, an upstream, a downstream, and a midstream station.[3] Notice that the temperatures at the downstream station are above those found at both the upstream and midstream stations for the majority of the early years. Over time this difference declines until the downstream temperature measures are very close to those made at midstream. This is an early signal that the large-scale restoration projects may be having a decreasing effect on summer water temperatures as envisioned by the restoration plan.

Figure 1.3: Water quality indicators along Johnson Creek



Similarly, we look at E. Coli measurements along Johnson Creek over time for evidence of improvements due to stream intervention projects.[4] E. Coli levels were measured at many sites along Johnson Creek. For ease of analysis we split the sites into two designations, sites upstream of the East Lents project and sites downstream of the East Lents project (see figure 1.2), and average the observed values of E. Coli by year. East Lents was used as a cutoff since it is near midstream, but downstream of the majority of the stream intervention projects. The results are depicted in the right-side panel of figure 1.3. In the case of E. Coli, downstream levels are initially much higher than upstream levels but decline over time until they are near or below upstream levels. This suggests that the stream intervention projects had the effect of decreasing E. Coli concentrations in the water. Overall, the water

[3]Temperature data is available through the U.S. Geological Survey from 1999-2013. The data obtained give monthly average water temperatures for each station. However for some months a particular station may be missing data. Thus, summer averages were calculated using only months where all three stations had an observation.

[4]Data courtesy of Portland BES.

and temperature data suggest that over time the downstream portion of Johnson Creek experienced improved water quality relative to the upstream portion of the creek. This improvement in downstream water quality may be due to stream intervention projects, such as Tideman-Johnson and East Lents, which were meant to improve water filtration and cooling along the stream.

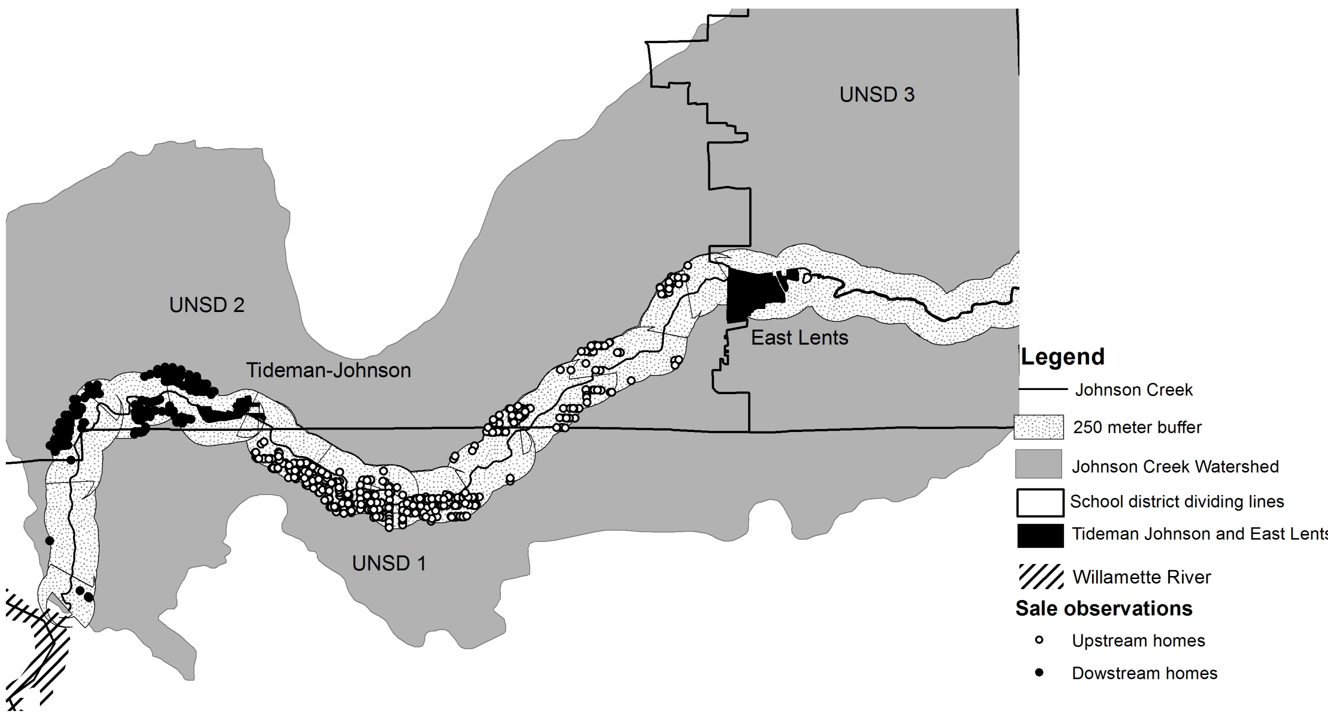
Direct evidence of the benefits of the Johnson Creek intervention projects in decreasing flood risk comes from the FEMA Flood Risk Report for Multnomah County [27]. This report shows the changes in Special Flood Hazard Areas (SFHA) along large portions of Johnson Creek over the past decade. While the amount of SFHA increased slightly overall in Multnomah County, the areas around Johnson Creek show a marked decrease is SFHA designation [27, pg. 31]. This decrease in flood risk along the Johnson Creek corridor is due, at least in part, to "changes in hydraulic structure", and "man-made changes to the watercourse" which may have occurred as a result of the stream intervention projects shown in figure 1.2. While the direct causal link between intervention projects along Johnson Creek and decreases in flood risk is still being established, Portland BES projects in the East Lents area, where flooding is most common, were designed to decrease the frequency of common floods by over 50% [76].

1.3.2 Data

Starting from an initial sample of all home sales from Clackamas and Multnomah counties in Oregon from 1990 to 2014, we first restrict the sample to only valid arms-length sales. All sales observations were assumed to be valid unless proven otherwise by one of the following criteria: sale was not an arms-length transfer, the home was not owner occupied, the home was 'flipped' meaning it sold twice within the same year, the home was part of a multi-parcel deal, the home was purchased by a company, the sale took place after a major renovation of the home. Additional data cleaning steps were: drop top 1% and bottom 1% of data based on sale price to eliminate outliers (as done by Muehlenbachs et al. [53]), drop homes that have a value of zero for square footage, drop homes that are within 100 meters of any of the major stream interventions as these homes would be subject primarily to direct amenity effects and not necessarily to the downstream water quality effect of interest, and drop homes that are *not* within 250 meters (m) of Johnson Creek. Homes in the final sample are thus in a 500m corridor along Johnson Creek, which causes both treated and control homes to be subject to any exogenous changes which affect the quality of the entire creek, such as a flood year, or changes in the amount of pollution flowing into the creek.[5]

We then split home sales into two sub-samples, the pre-intervention sample, and the post-intervention sample. Homes sales from the year the intervention took place were dropped due to the potential for externalities from project construction to negatively affect homes prices during that time. Tideman-Johnson is on the downstream portion of Johnson Creek

Figure 1.4: Home sales used in Tideman-Johnson estimation (1990-2014)



about three kilometers from where the stream merges with the Willamette River, as can be seen in figure 1.4. This is the urban area of the stream. The creek extends for many miles upstream, much of which flows through farmlands and foothills, areas that are fundamentally different from the downstream suburban regions. In order to reduce spatial heterogeneity we employ a "hard" (in the jargon of Abbott and Klaiber [3]) control for spatial heterogeneity and limit the upstream, control group of homes to those just upstream of Tideman-Johnson. Specifically, we use the school district dividing line just west of East Lents as the eastern border of our study area for the Tideman-Johnson case. This step also reduces the num-

[5]A 200m corridor was also tested with largely similar results, though in many cases the sample of homes within 100m of the creek is too small for statistical validity and thus 250m is used.

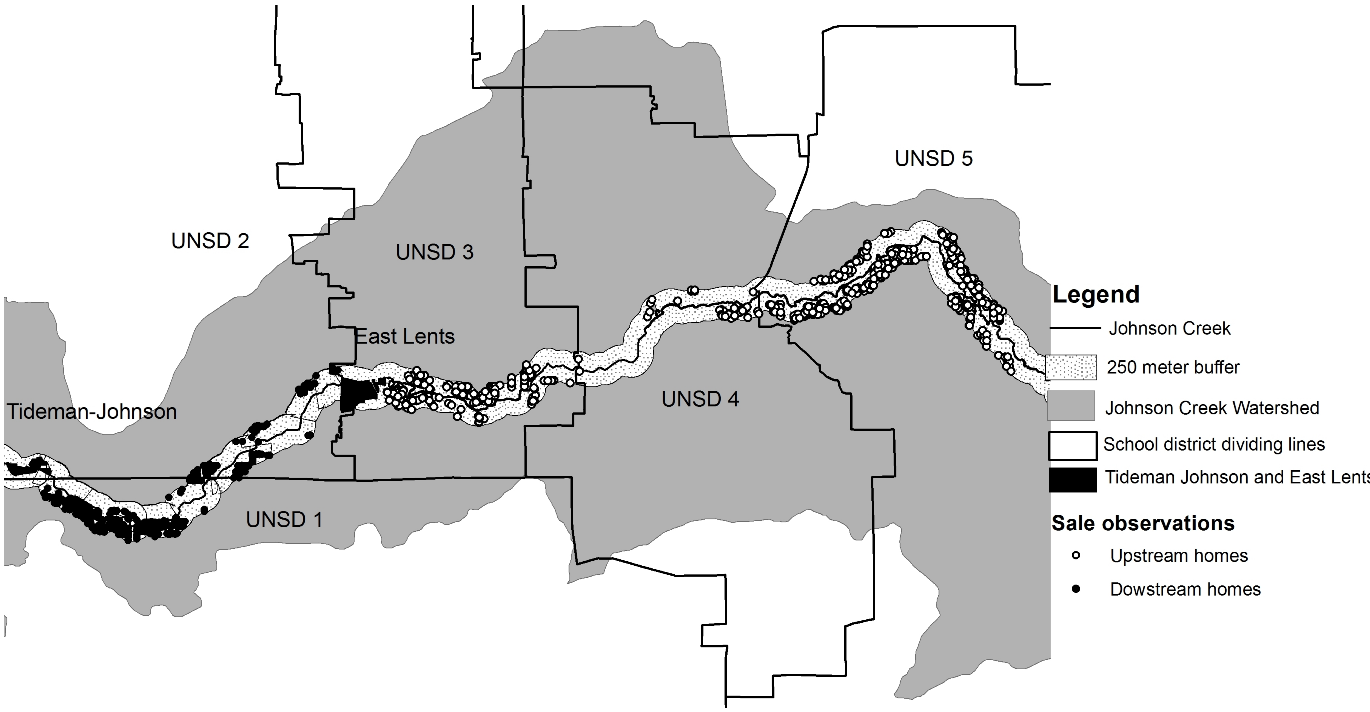
ber of school district effects that need to be controlled for. The sample of homes used in the Tideman-Johnson estimation, and their relation to the intervention and UNSD zones is shown in figure 1.4. Tables A.3 and A.4, in the Appendix, give observation counts, statistics on home characteristics, and price statistics by UNSD zone for the Tideman-Johnson estimation sample, split into pre-intervention (1990-2005) and post-intervention (2007-2014) sub-samples. From table A.3 we can see that downstream homes are generally larger and more expensive than upstream homes both before and after the intervention. Similarly, table A.4 shows that home values in UNSD 1 are generally lower than home values in UNSD 2. This disparity stresses the need to control for school district effects.

The data for East Lents estimation underwent the same cleaning procedure as the data for the Tideman-Johnson estimation. Tables A.5 and A.6, in the Appendix, give summary statistics and observation counts for the final sample of home sales used in the East Lents estimation. Notice that mean sales prices vary by upstream/downstream designation and by UNSD zone, suggesting that there may be unobserved spatial factors related to home values. For the sample used in the East Lents estimation, sale observations that were downstream of Tideman-Johnson were dropped from the sample. This is to ensure that the East Lents amenity effect is not confounded with the Tideman-Johnson effect. Furthermore, all sales observations prior to 1998 were dropped because these observations may be confounded with the Brookside intervention project (shown in figure 1.2), which took place in 1997 and is near the site of the East Lents project. As shown in figure 1.5, there are three UNSD zones which contain downstream homes (zones 1-3), and three zones that contain controls homes (zones 3-5). Thus, UNSD zones 1 and 2 contain only treated homes which necessitates the use of the 2SBCME to eliminate the spatial school zone effect for these treated homes.

1.3.3 Methods

Our matching estimation uses the nearest-neighbor difference in difference matching technique, similar to that employed by Muehlenbachs et al. [53] to estimate the home value impacts of hydraulic fracturing. In our application, homes downstream of an intervention project are considered treated, while homes upstream of the project are the controls. We base matching between treated and control homes on the following observed variables: square

Figure 1.5: Home sales used in East Lents estimation (1997-2014)



footage, number of bedrooms, number of bathrooms, propensity score[6], and sale year. These variables comprise the $\mathbf{x}_i$ and $\mathbf{x}_j$ vectors for treated and control homes, respectively. We will force two matches per downstream observation and allow for ties, so $n_i \geq 2$. We optimize the balance between treated and control samples by using the GenMatch algorithm of Diamond and Sekhon [24] to produce the vector of weights $\mathbf{W}$ in (1.1).

Implementing the difference in difference method to estimate the final ATT of the change in amenity value of Johnson Creek due to either of the two interventions for homes downstream of the project, we estimate two ATTs of being downstream (as opposed to upstream) of each project and their standard errors. The first is the pre-intervention ATT ($\hat{\tau}_0$) which is estimated using home sale observations from before the intervention took place, and measures the effect of being downstream of the project relative to control homes which are upstream of the project before the intervention. The second, post-intervention ATT ($\hat{\tau}_1$), measures the effect of being downstream, as opposed to upstream, of the project after the intervention.

[6]The propensity score is defined as the true probability of each unit receiving the treatment conditional on the covariates [31]. In our application it is the probability of a home being downstream of the project site. For our purpose this probability is estimated using logistic regression.

The difference between the pre-intervention and post-intervention ATTs is the ATT of the stream intervention that is of primary interest. To derive a standard error for the ATT of the intervention we employ a bootstrap method. Using the insight from Abadie and Imbens [1] that matching estimates are asymptotically normally distributed, we draw 1000 times from a normal distribution with mean $\hat{\tau}_1$ and standard deviation $\hat{s}_{\hat{\tau}_1}$. Similarly, we draw 1000 times from a normal distribution centered at $\hat{\tau}_0$ with standard deviation $\hat{s}_{\hat{\tau}_0}$. These standard deviations are estimated in the manner derived by Abadie and Imbens [1]. Differencing the vectors of draws from the two normal distributions gives an empirical distribution for the ATT of the intervention from which we can derive its mean and standard error. The difference in difference method gives an added safeguard against unobserved effects by eliminating time-invariant spatial heterogeneity between the downstream and upstream samples that manifests below the UNSD zone level.

To control for temporal confounding factors, we first adjust all home sale values for inflation to 2014 dollar equivalents. We then employ strategy (a) to eliminate temporal unobservables for all estimations by forcing exact matches on sale year in all estimations. This is crucial in our application since this exact matching on sale year will control for the effect of other large-scale interventions along Johnson Creek and exogenous changes to stream quality as waterway changes are hypothesized to propagate down the stream. Through exact matching on calendar year these exogenous changes should largely cancel out between treated and control observations.

We test and compare strategies (a), (b) and (c) from section 1.2 to control for unobserved spatial heterogeneity at the UNSD level. The 2SBCME in this case for the entire sample of treated homes is

$$\begin{aligned} \hat{y_{0i}} &= \tfrac{1}{n_i} \sum_{j \in \mathcal{J}_{i,n_i}} \left(y_{0j} - \hat{T}_{i,j} + \hat{\mu}_0\left(\mathbf{z}_i\right) - \hat{\mu}_0\left(\mathbf{z}_j\right) \right) \\ \hat{\tau}_{2SBCME} &= \tfrac{1}{N} \sum_{i=1}^{N} \left(y_{1i} - \hat{y}_{0i} \right), \end{aligned} \tag{1.16}$$

where the $\hat{T}_{i,j}$ terms are separately estimated ATTs which measure the discount (or premium) from being in the UNSD zone in which home i lies as opposed to the UNSD zone in which home j lies.

Similar to the difference in difference derivation, to carry through the first stage estimation uncertainty in the 2SBCME we compute the weighted average of individual $\hat{T}_{i,j}$ terms as can be inferred from (1.16). We then take 1000 draws from a normal distribution centered at this weighted average with standard deviation equal to the weighted average of the standard errors from the $\hat{T}_{i,j}$ estimations. These 1000 draws are differenced from the 1000 pre and post-intervention draws, since we estimate $\hat{T}_{i,j}$ terms for both the pre and post-intervention time periods. The draws of the pre and post intervention ATTs can then be differenced to elicit an empirical distribution of the ATT of the stream intervention of interest. The specifics of the first stage $\hat{T}_{i,j}$ estimations are given in the Appendix, section A.1.

Tideman-Johnson Methods

In the Tideman-Johnson case we have controls and treated homes in the two relevant UNSD zones (see fig. 1.4). Thus we can use strategies (a), (b), and (c) to control for unobserved spatial effects. Method (a) forces matches to be within the same UNSD zone, so treated homes in UNSD 1 can only be matched to control homes in UNSD 1, with the same going for UNSD 2. This method will eliminate any confounding school district factors but may come at the cost of poorer matches on other observable home characteristics and thus greater matching bias. Method (b) allows for matches between school zones and uses UNSD zone dummy variables as fixed effects in the auxiliary regression. Here only two UNSD zones have home sales observations, so we only need to include one fixed effect dummy variable in the bias-adjustment regression as this regression contains a constant term. We opt to include the dummy variable for UNSD 1 and let UNSD 2 be the omitted category. Note that we have control homes in both UNSD 1 and UNSD 2 which allows us to identify the UNSD fixed effect term in the auxiliary regression.

If we want to alleviate the burden on the auxiliary regression to estimate the fixed effects we can use strategy (c), the 2SBCME. This may be preferable in this case since we have relatively large samples of ineligible controls and relatively small samples of eligible controls, suggesting that the first stage of the 2SBCME may estimate the spatial effect more precisely than the auxiliary regression. We employ the estimator given in (1.16) with the relevant $\hat{T}_{i,j}$ terms measuring the spatial effect between UNSD 1 and UNSD 2. These figures are given in table A.1, in the Appendix.

For all Tideman-Johnson estimations the bias-adjustment regression uses the variables for bedrooms, bathrooms, square footage, and Euclidean distance to Downtown Portland[7] in the auxiliary regressoin. In the Tideman-Johnson case the vast majority of treated homes are closer to Downtown and the Willamette River from their control counterparts even when the control and treated homes are within the same UNSD zone. There is likely a premium on home value from being closer to the occupational and recreational opportunities of theses sites which would be unaccounted for by controlling for spatial effects at the UNSD level.

East Lents Methods

In the East Lents case, methods (a) and (b) are not feasible since we have no control homes in two of the school districts within which our treated homes lie. Specifically, UNSD zones 1 and 2 contain only downstream homes, as can be seen in figure 1.5. We cannot identify fixed effects terms in the bias adjustment regression for these two school districts since this regression is estimated using only matched control observations. Similarly, we cannot force matches to come from within the same UNSD zone as this would leave the vast majority of our treated homes with no match. To control for school zone effects then the *only* option is strategy (c), the 2SBCME. Two $\hat{T}_{i,j}$ terms are estimated for each upstream/downstream UNSD zone pair, one pre-intervention spatial ATT and one post-intervention spatial ATT. Due to the use of a difference in difference specification, these UNSD terms only effect the final ATT estimate if the estimated $\hat{T}_{i,j}$ terms vary between the pre and post-intervention periods. Time-invariant school zone effects will be eliminated due to the differencing of the pre-intervention ATT from the post-intervention ATT. Further detail on the estimation of these terms can be found in the Appendix, section A.1.

Since UNSD zones further down the stream are also closer to Downtown Portland, the $\hat{T}_{i,j}$ terms will account for the distance to downtown effect, on average, as one of the many amenities that vary at the UNSD level. To avoid double counting this distance to downtown effect we include only bedrooms, bathrooms and square footage in the auxiliary regression for all East Lents estimations.

[7]Downtown lies to the northwest and across the Willamette from our sample homes and is approximated by Portland City Hall.

1.3.4 Results

Tideman-Johnson Results

The estimation results of the effect of the Tideman-Johnson intervention on downstream homes are presented in table 1.1. Post-matching balance metrics are shown in table 1.2. Greater absolute values for the balance metrics denote poorer balance on the observed covariates between the treated and control sub-samples.

Column *(i)* of table 1.1 is included for comparative purposes, and gives the results from a matching model which does not include any control for UNSD zone effects. Column *(ii)* estimates of the table use strategy (a) for controlling for UNSD zone effects. Results in column *(iii)* are generated using strategy (b) to control for unobserved spatial effects. The balance statistics between specifications *(i)*, *(iii)* and *(iv)* are equal, as the matching algorithm is the same in all of these specifications. Comparing post-matching balance between these three specifications and model *(ii)* we can see that forcing matches to be within the same UNSD zone leads to poorer balance on some covariates. For instance, in the pre-intervention subsample forcing matches within UNSD zone nearly doubles the balance metrics of the square footage dimension, suggesting that specification *(ii)* has greatly decreased balance in this respect.

Specification *(i)*, which allows for matches across UNSD zone and thus has less matching bias but does not control for heterogeneous spatial effects, gives estimates that fall in between the estimates of specifications *(ii)* and *(iii)/(iv)*. This would suggest that the unobserved spatial effects are biasing the ATT estimates upward, but that bias from poor matches in *(ii)* may be more pronounced than the bias from omitted variables in *(i)* in this instance. Specification *(iii)* results in good balance between the treated and matched control samples, as shown in table 1.2, while still controlling for spatial confounding factors. The estimate from specification *(iii)* is also much lower than the other three estimates which is likely due to the small sample size of UNSD 2 controls which begets an imprecise estimate of the spatial effect. The post-intervention matched sample contains 86 unique controls from UNSD 1 and only 24 unique controls from UNSD 2. So it seems that strategy (b) is vulnerable to small sample problems as well.

To circumvent this issue we can use the 2SBCME, the results from which are given in column *(iv)* of table 1.1. The first stage of this specification uses ineligible controls to estimate

Table 1.1: ATT estimates of Tideman-Johnson effect on downstream home values in $000's

	No control for UNSD effects *(i)*	**Perfect Match Within UNSD** *(ii)*
ATT	30.20	34.70
Std. Err.	16.20	16.68
Lower 2.5% quantile	-1.78	2.18
Upper 2.5% quantile	61.88	67.49
	UNSD in Aux. Reg. *(iii)*	**2SBCME** *(iv)*
ATT	4.09	26.19
Std. Err.	16.23	16.45
Lower 2.5% quantile	-27.96	-5.80
Upper 2.5% quantile	35.84	59.11

All models match based on bedrooms, bathrooms, square footage and sale year, with bedrooms, bathrooms, square footage, and distance to Downtown Portland in the auxiliary regression.

the relevant UNSD zone effects. This allows for much larger sample sizes in estimating these effects.[8] Using the 2SBCME we estimate that the Tideman-Johnson project improved downstream home values by $26,190, on average. This amounts to 6.5% of downstream home values, which is reasonable based on the potentially substantial decreases in flood risk, among other benefits, experienced by these homeowners. However, this estimate, while strongly positive, is not statistically significant at the 5% level likely due to the high-degree of estimation uncertainty which is a result of small sample sizes for the second stage estimations and estimation uncertainty being carried through from the first stage.

East Lents Results

A summary of the ATT estimates for the effect of the East Lents project on downstream home values is given in table 1.3. To control for the unobserved spatial factors that vary at the UNSD level we employ method (c) and estimate the East Lents effect using the 2SBCME shown in (1.16). We include estimates from a specification which does not control for spatial unobservables in the first column of table 1.3 for comparative purposes. Details regarding the first stage estimations of the $\hat{T}_{i,j}$ terms are given in the Appendix, section A.1.

As can be seen in table 1.3, the specification which does not control for UNSD zone effects overestimates the ATT, compared to our preferred specification, suggesting that the unobserved effects may be biasing the estimate upward. The East Lents model in particular needs to account for UNSD effects since many of the control homes come from much

[8]Sample sizes for first-stage estimations given in table A.2, in the Appendix.

Table 1.2: Post-matching balance statistics of Tideman Johnson sample

Specification	**Balance metric**	**sq. footage**	**bedrooms**	**bathrooms**
Pre-intervention Model (ii)	normalized diff.	0.239	-0.01	0.221
	mean quantile diff.	178.547	0.214	0.208
Post-intervention Model (ii)	normalized diff.	0.154	0.118	0.039
	mean quantile diff.	108.78	0.402	0.065
Pre-intervention Model (iii)	normalized diff.	0.101	-0.081	0.155
	mean quantile diff.	86.457	0.143	0.139
Post-intervention Model (iii)	normalized diff.	0.165	-0.103	0.085
	mean quantile diff.	103.076	0.243	0.095

Normalized difference is the raw difference in variable means between treated and control sub-samples divided by the standard deviation of the treated as used by Ho et al. [32]. Mean quantile difference calculated as in Sekhon [68]. Post-matching balance metrics on sale year variable all equal zero since a perfect match is forced on this variable. Model *(i)* and *(iv)* have equal post-matching balance metrics as model *(iii)*.

Table 1.3: ATT estimates of East Lents effect on downstream home values in \$000's

	No Control For UNSD effects	**2SBCME**
ATT	30.05	20.02
Std. Err.	10.50	12.20
Lower 2.5% quantile	8.71	-5.19
Upper 2.5% quantile	49.40	42.72

All specifications base matching on square footage, bedrooms, bathrooms and sale year and include square footage, bedrooms and bathrooms in the auxiliary regression.

further upstream, where the surrounding areas are more rural and further from Downtown Portland, as can be seen in figure 1.5. Aside from the 2SBCME, there is no way to control for this spatial heterogeneity at the UNSD level since there are no control homes in two of the relevant UNSD zones. When we account for spatial factors using the 2SBCME the ATT estimate decreases, similar to what happens in the Tideman-Johnson case.

The results imply that the East Lents project improved the amenity value of Johnson Creek for homeowners downstream of the project site by \$20,020. This amounts to about 10% of the average post-intervention sale price of the treated homes, which is within reason given the synthesis of Braden and Johnston [14], which showed that water quality and flood risk can cause changes totaling up to 20% of home values. This value is larger than our preferred estimate of the Tideman-Johnson effect, however East Lents was a larger project, in terms of geographic area, and may have had a greater impact on flood mitigation than the Tideman-

Table 1.4: Post-matching balance statistics of East Lents sample

Specification	**Balance metric**	**sq. footage**	**bedrooms**	**bathrooms**
Pre-intervention	normalized diff.	-0.021	-0.062	-0.064
	mean quantile diff.	39.549	0.215	0.096
Post-intervention	normalized diff.	-0.065	0.044	-0.087
	mean quantile diff.	82.969	0.255	0.061

Normalized difference is the raw difference in variable means between treated and control sub-samples divided by the standard deviation of the treated as used by Ho et al. [32]. Mean quantile difference calculated as in Sekhon [68]. Post-matching balance metrics on sale year variable all equal zero since a perfect match is forced on this variable.

Johnson project as suggested by Portland BES [76][9]. However, again the estimate, while strongly positive, is not statistically significant at the 5% level likely due to large variances induced by small second stage sample sizes.

1.4 Discussion and concluding remarks

This paper explores the use of matching estimators when the conditional independence assumption does not hold due to the existence of unobserved spatial and temporal effects. Three strategies of controlling for these unobserved effects were discussed and compared including the introduction of the 2-Stage Bias Corrected Matching Estimator (2SBCME). All three strategies are viable, however the strategy chosen should be context specific and based largely on the relative sample sizes of control observations within a given spatial/temporal unit. All three strategies were illustrated in our application to the valuation of urban stream intervention projects. With small samples of eligible control observations within a spatial unit forcing perfect matches within the spatial unit leads to matching bias from poor matches. However, allowing matches across spatial units and estimating the spatial effect in the auxiliary regression did not perform well either, likely due to the small sample of controls used to identify the fixed effect terms.

The 2SBCME overcomes both challenges by allowing matches across spatial units, to improve

[9] Another possibility is that the East Lents intervention is fresher in the minds of nearby homeowners and potential buyers while the Tideman-Johnson effect has tapered off over time since our post-estimation time period for East Lents is only two years as opposed to 10 years for Tideman-Johnson. Indeed if we define the Tideman-Johnson post-intervention sample from 2007-2009 we find a higher ATT of $32,000.

match quality, and using the relatively large sample of ineligible control observations to estimate the spatial effects. In our estimation of the effect of the East Lents project the 2SBCME is the only available method for controlling for spatial heterogeneity due to the lack of eligible controls in two of the relevant spatial zones. The 2SBCME is a flexible method which can be employed to control for a variety of potential sources of unobserved effects through slight alterations to the framework shown in (1.16). Future research could use analytical and simulation methods to better understand the small sample properties of these estimators.

This research also provides a novel addition to the water valuation literature by estimating the effect of two stream improvement projects, Tideman-Johnson and East Lents, which took place along Johnson Creek, an urban stream running near Portland, Oregon, on home values for homes located *downstream* of the project sites. The results using the 2SBCME method show that both stream interventions likely had positive effects on downstream home values. In the Tideman-Johnson case these effects were estimated to be 6.5% of treated home values, while the East Lents project was estimated to have increased downstream home values by 10%. These estimates are thought to be reasonable given the potentially substantial decreases in flood risk experienced by downstream homeowners. Other positive impacts to homeowners are likely due to a combination of factors, including: improved water quality, an increase in desirable wildlife, improved access and amenity values of nearby open areas and parks, improved viewshed, and diminished odor from the stream. However, the precise causal mechanism by which stream improvements capitalize into home values is unclear; unveiling this mechanism would be a useful avenue for future research. Ancillary evidence from water quality indicators, and FEMA flood risk maps support the notion that the stream interventions brought about tangible improvements to Johnson Creek.

For applied researchers our results imply that the effects of a stream intervention project on adjacent homes can only be interpreted as a lower bound on the full positive impact of the intervention on all home values. To estimate the full impact on home values from an intervention project nearby homes, as well as homes downstream from the project, should be considered.

Chapter 2

The value of electricity supply security under global warming scenarios

2.1 Introduction

The synopsis of the recent IPCC (Intergovernmental Panel on Climate Change) report made clear that global temperature increases and other climactic changes will have substantial effects on the economic well-being of the global citizenry [37]. Aggregate economic loss from an optimistic 2 °C increase in temperature is predicted to be in the range of 0.2% - 2% of world GDP and will likely be closer to 2% [37]. A decrease in levels of electricity supply security may constitute a part of the economic loss from climate change if preventative steps are not taken. The predicted climactic changes of increased temperatures, increased winds and storms, extreme high temperatures, and ice storms, can cause damage to the electricity grid and subsequent power outages [36, ch. 10]. Thus, climactic changes will increase the challenge for policy makers and grid operators to maintain grid stability. However, the IPCC report also lists numerous adaptations that can reduce the damage to grids, such as rerouting transmission lines, installing external coolers to transmission components, and enhancing stability standards for pylons. These adaptations will be costly and thus should be installed in regions where there is great risk for climate related grid damage and regions where power outages will have the largest negative welfare effects. As an input for informed grid adaptation, welfare impacts from power outages, both currently and in the future, must be known.

This research estimates economic impacts to households from power outages for 19 nations in the European Union (EU) and, for the first time, works towards an understanding of the interconnection between temperature and the value of supply security. Past research has shown that the relationship between electricity usage and temperature is U-shaped, since as temperatures get more extreme ambient heating and cooling devices are used to a greater degree [e.g. 9, 13, 47]. We posit that a similar relationship exists between temperature and the value of supply security. Using survey data from a choice experiment administered over 19 EU nations, we test the relationship between temperature and WTP (willingness to pay) to avoid a power outage. Since our choice experiment explicitly states the month of the power outage (July or January), respondents who are cognitively engaged with the survey will consider the temperatures they often experience in these months when they respond to the WTP questions. Indeed, the results show that local seasonal temperatures are strong drivers of a household's WTP to avoid a power outage. We use a hierarchical Bayesian modeling framework which allows parameter estimates to vary by season to show that increased temperatures in the summer increase WTP while increased temperatures in the winter decrease WTP.

Current EU plans to invest in a renewable energy grid will effect supply security for years to come [26]. To better inform the long-term planning of the EU grid we use the econometric model relating temperature measures to WTP to impute future hourly WTP under three global warming scenarios across our 19 sample nations. These results show how the spatial distribution of hourly WTP will change in the future with the most significant change being the increase in welfare losses from summer power outages across much of Southern and Central Europe. These results can also be used at a finer spatial scale to aid in the planning of regional electricity grid development. Furthermore, we predict WTP into the future based on predicted temperature changes to examine the expected trends in welfare losses from power outages overall. This exercise shows that, on average, per household hourly welfare losses from power outages will increase, suggesting that global warming will increase the importance of electricity supply security. These predictions can be used in cost-benefit analyses to work towards a socially optimal level of supply security in the EU, both currently and in the future.

We proceed with a brief discussion of related literature and the Bayesian techniques used in the estimation. We then describe the choice experiment survey data and temperature measures used for estimation. Next, we relate the results from the econometric model and the imputations, which predict hourly WTP in the future across 19 European nations.

2.1.1 Related literature

Previous studies have investigated the value of electricity supply security in the EU, but to date none have considered the effect that temperatures have on this valuation. Some of these studies have estimated the value of supply security for individual EU nations [55, 64, 63, 46]. Results from these analyses suggest that the value of supply security to residential consumers varies based on the duration of the outage, season and day of the week on which the outage takes place [64, 46]. The VoLL (value of lost load), which measures the average economic damage per kWh of electricity not delivered due to a power outage, is another prevalent measure of the value of supply security along with the WTP to avoid the power outage. The VoLL is estimated using the 'production function' approach, which estimates the value of time lost or underutilized due to power outages for residential consumers. This technique uses aggregate economic data, whereas our method, estimating the WTP to avoid an outage, uses information at the household level which allows us to account for heterogeneity between households with respect to their vulnerability to outages.

The VoLL of a select few EU countries has previously been estimated, these figures are averaged across households and across time of day. In the Netherlands Nooij et al. [55] estimated a VoLL of €16.40 per kWh not supplied for a 1 hour outage. Praktiknjo et al. [59] find that a 1 hour outage elicits a VoLL of €15.70 per kWh not supplied to household consumers. In the case of Ireland, Leahy and Tol [46] estimate a VoLL of nearly €25 per kWh not supplied to Irish households. Methodological differences between these studies makes it difficult to accurately compare the value of supply security across nations. This paper presents, for the first time, a full cross-sectional comparison of the value of supply security across 19 EU nations, using consistent data collection and econometric methodology.

With regard to the relationship between electricity use and temperature, past research has confirmed that changes in temperature drive changes in household electricity consumption [e.g. 9, 13, 47]. Confirmation of this link is unsurprising given that nearly 65% of household energy consumption in the EU is used for space heating [44]. Bessec and Fouquau [9] showed empirically, for the case of 15 EU nations, that temperature is a significant determinant of electricity consumption, and that the relationship between temperature and electricity use is U-shaped. The threshold value where temperature increases begin to positively influence electricity use is between 10 and 20 °C [9]. Similarly, Lee and Chiu [47] find evidence for a strong U-shaped relationship with a 12°C threshold value using data from 24 OECD countries. With respect to electricity demand under global warming, the IPCC report's general conclusions are that in high-income nations, temperature increases will be the dominant factor driving future changes [36, ch. 10]. Energy use is expected to rise in regions with higher temperatures and fall in regions with lower temperatures, largely due to changes in the use of climate control systems. From this, one could infer that supply security will become more valuable in hotter regions, and potentially less valuable in cooler regions. The research presented herein will empirically examine this inference and allow for a quantitative assessment of the change in the value of supply security due to changes in temperature.

2.2 Model

We test the relationship between temperature measures and WTP for supply security by estimating a hierarchical Bayesian model using data from a choice experiment survey, the details of the survey and sample are given in section 2.3. The novel parameters of interest which flow from this model are the slope coefficients relating local temperatures to the respondent's WTP for supply security. We use these slope coefficients to predict changes to the value of supply security under global warming scenarios across 19 EU nations.

We specify each respondent i's indirect utility representation for two cases for each choice menu $s \in \{1 \dots S\}$: in the event of a power outage with the characteristics stipulated by menu s denoted as $\tilde{v}^*_{is}$, and in the event that they pay to avoid such an outage denoted as $\tilde{v}_{is}$.

$$\begin{aligned} \tilde{v}^*_{is} &= \gamma_i m_i - d_s \mathbf{D}'_s \beta^*_{is} + d_s \tilde{\epsilon}_{is} \\ \tilde{v}_{is} &= \gamma_i (m_i - P_{is}) + d_s \tilde{\epsilon}_{i0} \end{aligned} \tag{2.1}$$

Where m_i is the household income of respondent i, P_{is} is the bid price entered as a positive number, and d_s is the outage duration measured in hours. The vector $\mathbf{D}$ holds our season indicators, which allows for season-specific marginal effects; season refers to either winter or summer which are represented by single months, January and July, respectively. The error terms capture scenario-specific factors that are unobserved yet affect utility. The error terms are scaled by the duration of the outage d_s, to account for the larger variance in indirect utility associated with longer outages. Lengthy outages expose individuals to a wider variety of potential nuisances with greater extremes. For instance, a short outage may ruin a meal in the midst of being cooked, while a longer outage could ruin a series of meals that would have been cooked *and* spoil the entire freezer full of food. We can show the model in "utility-space" by subtracting the above two utilities.

$$v_{is}^* = \tilde{v}_{is} - \tilde{v}_{is}^* = d_s \mathbf{D'}_s \beta_{is}^* - \gamma_i P_{is} + d_s(\tilde{\epsilon}_{i0} - \tilde{\epsilon}_{is}) \tag{2.2}$$

We elect to estimate this model in "surplus", or "WTP-space" for ease of interpretation and estimation. Thus, we divide through the previous equation by the marginal utility of income γ_i. This yields v_{is} which can be interpreted as the difference between the full WTP to avoid the outage in menu s and the bid price to avoid the outage. We will observe a positive response to the survey question when $v_{is} > 0$ indicating that the respondent increases their utility by paying the bid price rather than experiencing the outage.

$$\begin{aligned} v_{is} &= \frac{v_{is}^*}{\gamma_i} = d_s \mathbf{D'}_s \beta_{is} - P_{is} + d_s \epsilon_{is} \\ \epsilon_{is} &= \frac{(\tilde{\epsilon}_{i0} - \tilde{\epsilon}_{is})}{\gamma_i} \quad \text{where} \quad \epsilon_{is} \sim n(0, \sigma_i^2) \\ \beta_{is} &= \frac{\beta_{is}^*}{\gamma_i} \end{aligned} \tag{2.3}$$

Previous studies have found that estimations in WTP-space perform better than those in utility-space by avoiding excessively long tails on predicted WTP [70, 67]. These long tails arise due to the fact that in a utility space model, as in (2.2), marginal WTP is derived as $\frac{\beta_{is}^*}{\gamma_i}$. With a very small income parameter (γ_i), as is often the case, an inflated WTP estimate can arise. By using the WTP-space method in (2.3) we avoid this problem and estimate one parameter (β_{is}) for the marginal WTP. As shown by the simulations in Sonnier et al. [70], this WTP-space specification produces more accurate estimates for a variety of specifications. However, this modeling choice comes at the expense of not being able to estimate the marginal utility of income γ_i, independent from other parameters. However, γ_i is not a construct of interest in our present analysis. Also note from (2.3) that we allow for heteroskedasticity at the respondent level (σ_i^2) through respondent-specific random effects.

From (2.3) our parameter of interest is β_{is} which can be interpreted as the marginal hourly

WTP of person i when confronted with outage scenario s. Next we add structure to β_{is}, that is:

$$\begin{aligned}\beta_{is} &= \left(1 + \mathbf{z}_{is}\boldsymbol{\alpha}'\right)\beta_i \\ &= \left(1 + \alpha_1 z_{i1} + \alpha_2 z_{i2} + \ldots + \alpha_k z_{ik}\right)\beta_i \\ &\text{where } \tilde{\beta}_i = \bar{\beta} + \delta_i, \\ &\text{and with } \delta_i \sim n(0, \nu^2).\end{aligned} \tag{2.4}$$

Thus, β_{is} is expressed as a function of observable and unobservable (β_i) characteristics. Where $\mathbf{z}_{is}$ is our vector of observed variables that explain an individual's deviation from mean marginal WTP. These observable characteristics come in two forms, those that are respondent specific, indexed by i, and one scenario specific characteristic, indexed by s. The one scenario specific characteristic is an indicator variable which takes a value of one if the scenario s referenced an outage which affects the entire country of individual i as opposed to just their local area. We call this variable "*wholecountry*," in the empirical section below. Also included in $\mathbf{z}_{is}$ are country indicator variables that account for unobserved heterogeneity in WTP for supply security between nations. All variables included in $\mathbf{z}_{is}$ are centralized around their respective mean to allow interpreting $\bar{\beta}$ as mean WTP over all respondents and all scenario characteristics, and to achieve better mixing properties of the Markov Chain Monte Carlo (MCMC) sampler. The $\boldsymbol{\alpha}$ vector contains one coefficient for each of our k explanatory variables and relates these variables to deviations in marginal WTP. The average estimated hourly WTP to avoid a power outage is represented by $\bar{\beta}$, and δ_i captures individual-specific unobserved heterogeneity in deviations from $\bar{\beta}$.

Let $\mathbf{y}_i$ be the vector of observed binary responses of individual i to each menu $s = \{1 \ldots S\}$ where a 1 denotes that the respondent accepted the bid price and a 0 denotes rejection of the bid price. A response of 1 will be observed when $v_{is} > 0$. From the error specification in (2.3) we can write the marginal likelihood as a standard normal cumulative distribution function (cdf) conditioned on β_{is} and σ_i^2.

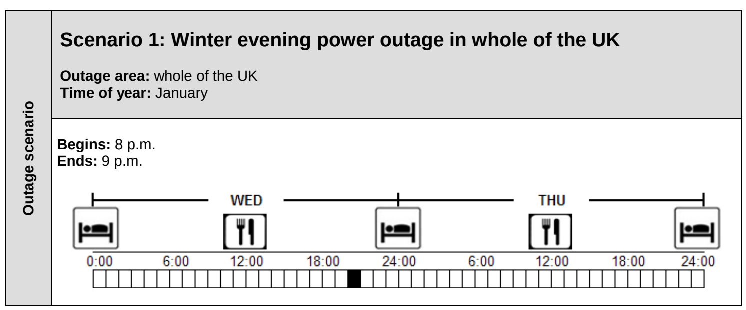
$$prob(y_{is} = 1 | d_s, \mathbf{D}, P_{is}, \beta_{is}, \sigma_i^2) = prob(v_{is} > 0 | d_s, \mathbf{D}, P_{is}, \beta_{is}, \sigma_i^2) = \Phi\left(\frac{1}{\sigma_i}(d_s \mathbf{D}'_s \beta_{is} - P_{is})\right) \tag{2.5}$$

Where Φ represents the normal cdf. Using this likelihood we then draw from the posterior distribution via a Gibbs Sampler. More detail on the sampling is given in the Appendix, section B.1.

2.3 Data

Data for this analysis come primarily from a survey conducted for the SESAME (Securing the European Electricity Supply Against Malicious and Accidental Threats) research project. The survey was conducted during the last two quarters of 2012 and the first quarter of 2013 in all EU-27 nations.[1] The survey was given both as an internet survey and on the phone with supplementary materials sent to phone-respondents via post. This massive survey effort, encompassing over 13,000 interview hours and over 400,000 contact attempts, yielded over 8,000 completed questionnaires with around 300 survey responses per nation. Substantial effort was exerted to ensure that the final sample was representative of each nation's population in the dimensions of gender, age, working status, income, and rural residents. The survey obtained demographic, energy usage, and energy perception information from each individual, and included a choice experiment designed to elicit respondent's WTP to avoid blackouts with certain characteristics. The choice experiment portion of the survey asked respondents to imagine a power outage with a specified duration, start and end time, month, and area (residential street or whole country). A visual depiction of one of the eight scenarios shown to respondents is reproduced in figure 2.1. There were two months represented in the survey, January, and July. The survey used 1 hour, 4 hours, 12 hours and 24 hours as durations of the outage scenarios, generally reflecting the durations found in literature [45, 20, 19, 7, 64]. Since the number of choice tasks is limited to eight due to length and budgetary constraints, we reveal two scenarios for each duration length to every respondent. The characteristics of all eight scenarios are shown in table 2.1.

Figure 2.1: Example of blackout scenario from the English/UK version of the survey



After seeing a depiction of a power outage scenario respondents were offered the option to

[1] See Gutierrez et al. [29] for a detailed account of survey methodology and the English version of the full questionnaire.

Table 2.1: Characteristics of the eight blackout scenarios encountered by survey respondents

Scenario	**Duration**	**Summer(S) or Winter(W)**	**Residential (R) or Whole country (C)**
1	1	W	C
2	24	W	C
3	4	S	C
4	12	S	C
5	24	W	R
6	4	W	R
7	12	S	R
8	1	S	R

Scenarios were presented in a rotating order, a scenario number is given as a reference.

pay a specified amount of money in their native currency to avoid experiencing the outage. This is referred to as the 'bid price' (P_{is}), which varies for each respondent and with a total of four possible bid prices per scenario and country. The bid price design is based on a previous, similar WTP study conducted by Reichl et al. [64] for the nation of Austria, which used the D-optimality criterion with balanced utilities to set the bids [33, 18]. Two of the four bids of each scenario used in the Austrian study are adopted here with a correction for the difference in income distribution between Austria and every other nation. The other two bids of each scenario are held constant between countries to enable cross-country comparison. As expected, the survey results show that a decreasing proportion of respondents are willing to pay as the bid price increases as shown in table 2.2. The initial survey sample of 64,536

Table 2.2: Proportion of respondents who accepted the offered bid by scenario

	Scenario							
	1	2	3	4	5	6	7	8
Lowest bid	0.65	0.80	0.59	0.54	0.62	0.63	0.55	0.39
Low bid	0.48	0.68	0.47	0.40	0.60	0.48	0.47	0.18
High bid	0.34	0.44	0.25	0.34	0.35	0.25	0.39	0.09
Highest bid	0.28	0.32	0.20	0.18	0.33	0.20	0.22	0.10

N=7741; from full sample across all EU-27 nations and all complete survey responses

complete observations from 8,067 different respondents (8 scenarios per respondent) was reduced due to responses of "don't know" to one or more of the survey questions used in the statistical model. The sample of usable observations consists of 61,928 observations from 7,741 different respondents.

In order for respondent to be linked with the relevant temperature data their location had to be approximated. The first step in this process was geocoding, or giving a cartographic point to a respondent's location. Beginning with our sample of usable survey responses, 43% of these questionnaires were completed online, leaving us with no location information for these respondents. For the respondents that used phone and postal media we were able to obtain the first seven digits of their phone numbers (including country code) and occasionally an address fragment which contains either a postal code or city name from the survey company. For legal reasons and privacy protection of survey participants full addresses could not be obtained. As this study is concerned with broad temperature trends we use aggregated temperature measures in our statistical model. Therefore, precise geocoding is not necessary since in most cases this data aggregation will average away measurements errors from incorrectly placed respondents. Based on the data we obtained from respondents and the spatial data available at the European level, we attempted to match every respondent to a postal code region. The only free-to-use cartographic data on postal codes known to the authors come courtesy of *geonames.org*. These data estimate the centroid of each postal code area with a coordinate point, and are available for 21 nations out of the EU-27.

Of the 4,605 respondents who used telephone and postal media for the survey we were able to obtain address fragments for about 1,900 of them, although these fragments were not always useful for matching the respondent to a postal code. We then manually linked telephone area codes to postal code regions for each country. Every nation has a different system and standards in place for postal codes and telephone area codes leading to varied levels of precision in converting area codes into postal codes. In general, area codes define larger areas than postal codes. In cases where one area code matches to multiple postal codes effort was made to choose the postal code with the highest population to increase the chance the postal code is correct. Thus, at worst the geocoded respondent location is in the correct area code region, and at best in the correct postal code region.

The union of our ability to geocode respondents based on area codes and the availability of gecoded postal regions from *geonames.org* dictated our final estimation sample. This sample consists of data from 19 EU nations, the number of respondents varies between nations based on the exact number that used phone and post media for their survey response and our ability to geocode their locations. The number of respondents in each nation and a summary of their characteristics is shown in table 2.3. Some respondents gave cellular phone numbers which cannot be referenced geographically. There were especially high proportions of respondents using cellular phones in Sweden and Finland, which is the reason for the smaller sample sizes in these nations. Respondents located outside of continental Europe, such as those on Atlantic islands, were dropped to avoid convoluting their responses with those from the mainlands of their nations where power supply and provision may be fundamentally different.

Table 2.3: Cross-country comparison of sample means

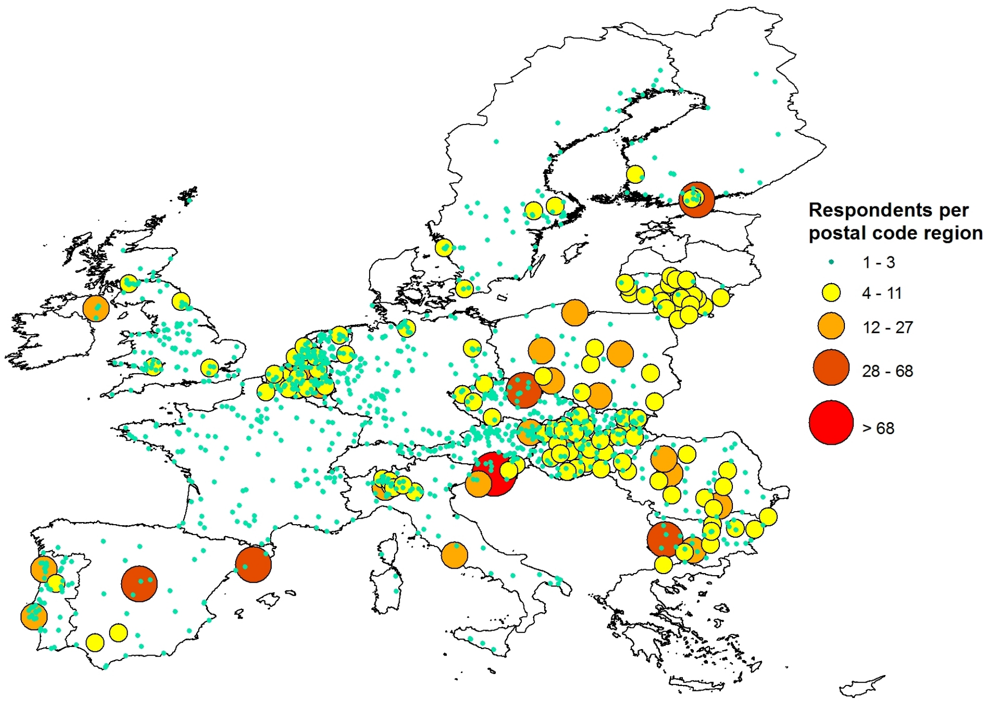
	income	*male*	*age*	*hhsize*	*college*	*urban*	*numoutages*	*no. respondents*
France	30,006	0.44	51.17	2.75	0.40	0.18	3.37	158
Germany	31,181	0.59	57.75	2.55	0.51	0.08	1.17	130
Italy	24,300	0.40	54.64	2.68	0.30	0.32	3.43	161
UK	26,661	0.50	53.41	2.88	0.35	0.10	2.06	146
Austria	29,235	0.56	53.86	3.03	0.31	0.13	2.62	151
Belgium	26,718	0.53	50.10	2.48	0.52	0.42	1.86	173
Finland	27,753	0.47	61.49	1.88	0.41	0.13	2.54	83
Netherlands	21,753	0.47	55.48	2.01	0.24	0.20	1.10	154
Spain	22,177	0.51	53.66	2.97	0.46	0.53	2.86	148
Sweden	26,012	0.65	58.80	1.94	0.34	0.15	1.43	99
Portugal	15,643	0.52	52.77	2.99	0.32	0.30	3.87	119
Bulgaria	4,139	0.37	52.58	2.70	0.59	0.63	5.41	132
Czech	10,239	0.51	56.66	2.59	0.45	0.28	2.74	136
Hungary	5,399	0.33	57.64	2.70	0.31	0.10	5.23	172
Lithuania	5,515	0.28	55.38	2.65	0.62	0.11	2.56	151
Poland	7,141	0.47	57.33	2.77	0.42	0.41	3.62	159
Romania	3,196	0.44	55.61	2.76	0.48	0.52	7.38	140
Slovakia	7,556	0.39	55.86	2.88	0.37	0.24	3.19	156
Slovenia	14,832	0.41	57.07	2.76	0.30	0.29	2.63	161

2,729 total respondents; age mean constructed from 4 age categories by taking the middle value of each category and using 68 for those over 60; variables are defined in table 2.4

The final sample contains complete information for 2,729 respondents with 8 observations per respondent (1 per outage scenario), leaving a total of 21,832 observations. The spatial distribution of our final sample of respondents is shown in figure 2.2 where larger circles represent a greater number of respondents being placed at the same postal region centroid. Thus, the figure also shows the level of spatial variation in our sample where some nations have only a few large circles present, such as Slovenia, which indicates low intra-country variation in location and thus temperature measures, while other nations have many small circles, such as Germany, which indicates high intra-country variation in location and temperature variables.

Explanatory variables used in the statistical model ($\mathbf{z}_{is}$-vectors) are defined in table 2.4. The cross-country comparison of sample means in table 2.3 shows the high level of heterogeneity across the 19 EU nations in our sample in many respects, most notably average income

Figure 2.2: Geocoded respondents by postal code centroid



and the average number of outages experienced in the past year. Since we use category indicator variables in our $\mathbf{z}_{is}$-vectors one variable from each category had to be omitted to avoid perfect collinearity. The omitted category for the age groups are those younger than 35; the omitted category for the experienced outage duration are those who experienced an outage that lasted less than one hour or did not experience an outage at all; the omitted category relative to the *urban* variable are those who live in suburban or rural settings.

2.3.1 Temperature Measures

Data on temperature come from the European Climate Assessment and Dataset (ECA&D) ENSEMBLES project "E-OBS" dataset which, to our knowledge, is the only European wide, daily temperature dataset available for the European Union [30]. This dataset takes the form of a 0.25° lat-long grid across all of Europe where the temperatures at each grid point are imputed based on observed temperatures from weather stations across the continent, taking

Table 2.4: Summary statistics of explanatory variables in **z**-matrix

Variable	Description	Mean	Std. Dev.	Min .	Max.
urban	lives in urban area	0.27	0.45	0	1
male	is male	0.46	0.50	0	1
age35t45	between age 35 and 45	0.18	0.39	0	1
age46t60	between age 46 and 60	0.36	0.48	0	1
over60	over age 60	0.41	0.49	0	1
hhsize	members in household	2.66	1.24	1	6
college	college degree	0.40	0.49	0	1
out1t4	experienced 1-4 hour outage	0.32	0.47	0	1
out4t8	experienced 4-8 hour outage	0.12	0.32	0	1
out8t24	experienced 8-24 hour outage	0.07	0.26	0	1
over24	experienced over 24 hour outage	0.04	0.20	0	1
numoutages	number of outages in past year	3.14	4.42	0	25
rotation	outage scenario ordering	0.51	0.50	0	1
wholecountry	outage effects entire country	0.50	0.50	0	1

21,832 observations from 2,729 respondents; $\mathbf{z}_{is}$-vectors also contains country indicator variables

into account elevation. The data include daily mean, maximum, and minimum temperatures for our time period of interest (2012-2013) for 8,855 grid points across the EU-27 and 8,173 grid points within our 19 sample nations. The four closest grid points are matched to each respondents based on Euclidean distance. All temperature measures associated with each respondent are then calculated as the average of the relevant temperature measure between the four matched grid points. The average of four points is used, as opposed to just the closest point, as a smoothing technique to reduce idiosyncratic variation in temperature measures between respondents as a result of our inexact respondent geocodes. Thus, the temperature measures linked to each respondent relate temperatures in the area of the respondent, which is also consistent with the possibility that respondents envision themselves in locations other than their home in hypothetical outage scenarios (e.g. at work or in an entertainment district).

We created and tested several temperature measures in the statistical model to ascertain which temperatures are relevant to respondents when they take the survey. Since each outage scenario specifies a month, either January or July, in which the outage occurs, it is reasonable to assume that survey respondents are recalling past January or July temperatures when they assess their WTP to avoid a given outage. Thus, respondents are initially linked to temperatures from the most recent January or July with respect to their survey date. For instance a respondent who took the survey in February 2013 would be linked to January 2013 and July 2012 temperatures. A respondent who took the survey in July 2012 would be linked to July 2012 and January 2012 temperatures.

All temperature measures are monthly averages that are calculated from the daily values given in the E-OBS dataset. Other tested temperature measures average the monthly averages over the past ten years to measure the longer-term temperature that respondents associate with a particular month in their region. The final temperature measure tested is degree days, which are widely used in the energy industry as a basic representation of the amount of time indoor climate control will used. Degree days have also been used in lieu of direct temperature measures in empirical analyses of the energy sector, as these measure inherently account for nonlinearity in the effect of temperatures on electricity use [e.g. 77, 78, 56]. In our measure of degree days, we employ the commonly used 18°C threshold at which temperatures begin to cause increases in electricity use [9]. The method used calculate degree days is shown in (2.6) and follows closely that used by Blazquez et al. [13].[2]

$$\begin{aligned}
&\text{Heating degree days:}\\
&dd_k = \begin{cases} 18 - t_k & \text{if} \quad t_k \leq 15 \qquad (1) \\ 0 & \text{if} \quad t_k > 15 \qquad (2) \end{cases}\\
&\text{Cooling degree days:}\\
&dd_k = \begin{cases} t_k - 18 & \text{if} \quad t_k \geq 22 \qquad (1) \\ 0 & \text{if} \quad t_k < 22 \qquad (2) \end{cases}
\end{aligned} \tag{2.6}$$

Where t_k is the observed daily mean temperature on day k from the E-OBS data, and dd_k are degree days for day k.

A comparison of all the temperature measures we test in our empirical model is given in table 2.5. As can be seen from the table, the measures are highly correlated which suggests that only one, or possibly two, measures should be included in the model to avoid losses of efficiency due to multi-collinearity.

While we estimate our statistical model using each of the temperature measure shown in table 2.5, our preferred measure is the daily average over the past ten years. This measure is created by first averaging the daily average temperature from E-OBS data over the relevant months (January and July), and then averaging these monthly averages over the past ten years from the survey date. This yields long-term temperature measures which are intuitively

[2]Note that in the summer month of July only cooling degree days are considered while in the winter month of January only heating degree days are considered.

Table 2.5: Summary statistics of relevant temperature measures (°C)

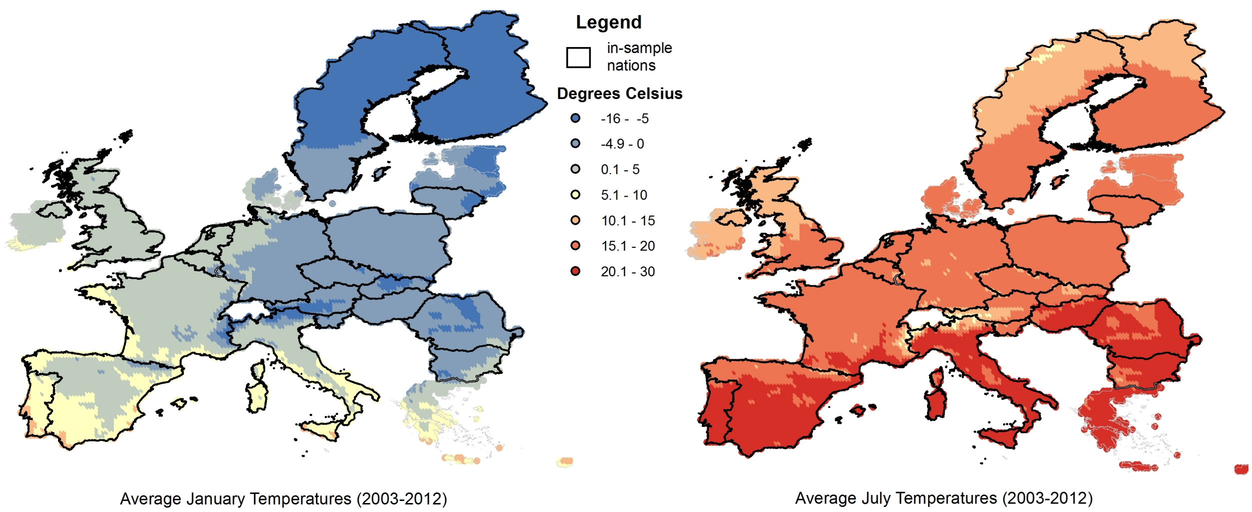
Temperature Measure	Mean	Median	Min	Max	Std. Dev.	Correlation with daily avg. over past 10 yrs.
January (winter) Temperatures						
Daily avg. over past 10 yrs.	-0.38	-1.55	-13.34	11.22	4.02	1.00
Daily min over past 10 yrs	-3.71	-4.54	-18.55	8.51	4.11	0.99
Daily max over past 10 yrs	2.83	1.64	-8.87	15.28	4.15	0.99
Daily avg. previous year	1.76	1.30	-12.66	12.54	3.96	0.96
Avg. monthly degree days over past 10 yrs.	569.60	606.13	208.44	971.48	124.83	-0.99
Daily avg. on day of survey	8.75	9.16	-25.03	23.31	6.64	0.40
July (summer) Temperatures						
Daily avg. over past 10 yrs.	18.65	17.93	8.05	27.10	2.81	1.00
Daily min over past 10 yrs	13.31	12.94	4.52	20.21	2.18	0.92
Daily max over past 10 yrs	23.99	23.32	11.99	35.60	3.36	0.97
Daily avg. previous year	20.13	19.66	9.86	27.63	3.36	0.94
Avg. monthly degree days over past 10 yrs.	39.56	13.53	0.00	280.66	53.88	0.92
Daily avg. on day of survey	8.75	9.16	-25.03	23.31	6.64	0.22

N = 2729 ; All measures are monthly averages calculated from the daily E-OBS data

more compatible with our study, given that future climate predictions are often made in 10 or 20 year intervals, and the long-term nature of electricity grid planning and investment. However, given the strong correlation between temperature measures, using daily averages over a ten year horizon does not greatly alter the results versus using extreme temperatures over ten years, or only past year temperatures. Figure 2.3 shows the daily averages over the past ten years (2003-2012), for the two relevant months, across the EU-27. As can be seen in the figure, the monthly averages in July only exceed the 22°C cooling degree day threshold in the southern, "Mediterranean" parts of Europe, while the January means fall below the 15°C heating degree day threshold for the majority of the continent. This illustrates why climate control in the winter is more relevant for European energy consumption.

As an additional exercise, we estimate the model using as the temperature variable the mean daily temperature in the region of each respondent on the day they took the survey. This will serve as a check for the level of cognitive engagement in our surveyed respondents; if they are responding to the environment they are currently experiencing or if they are able to abstract from this environment and put themselves in the hypothetical scenario that the survey creates.

Figure 2.3: Monthly average temperatures across the EU-27 calculated from daily averages of E-OBS data



2.4 Results

The marginal effects for the respondent and scenario specific variables included in $\mathbf{z}_{is}$, shown in (2.4), are given in table 2.6. Recall that in Bayesian econometrics a posterior distribution of each parameter is the estimation output. The "mean" column of table 2.6 gives the mean of this empirical distribution for each marginal effect which can be interpreted as the change in hourly WTP from a one unit increase in the respective variable. The "prob>0" columns in table 2.6 and elsewhere show the proportion of the density that falls to the right of zero, and thus provides an at-a-glance indication for if a given marginal effect is predominantly positive, negative, or indeterminate. Also shown are the 5% and 95% quantiles of the distributions of each parameter to relate the variance of the marginal effects estimates; these quantiles are calculated via the Highest Probability Density method.

The marginal effect of the *urban* variable shows that residents of urban areas are willing to pay more to avoid power outages, likely due to concern that the outage would effect nearby desirable infrastructure, such as hospitals or traffic systems. The results from the demographic variables suggest that older residents are willing to pay more while males are willing to pay less. The marginal effects of household size and college education are considered inconclusive. A respondent's history with power outages is also shown to drive their WTP, as respondents who have recently experienced a long outage (over 4 hours) are WTP less to avoid future outages. This is likely due to a readiness factor whereby these respondents have prepared for future outages by, for example, buying flashlights, candles or perhaps even a generator, and thus will be less effected by future outages. The scenario specific variable *wholecountry* shows by far the largest marginal effect on WTP and demonstrates that outages which affect a larger geographic region have a larger negative welfare impact. This is again likely due in part to the loss of valued infrastructure outside the home, and perhaps altruism where the respondents are concerned with the effects of the outage on friends and family.

Table 2.6: Marginal effects of explanatory variables on hourly WTP in Euros

	Winter				**Summer**			
	5% quantile	**mean**	**95% quantile**	**prob> 0**	**5% quantile**	**mean**	**95% quantile**	**prob> 0**
urban	-0.0053	0.0012	0.0080	0.62	0.0007	0.0130	0.0253	0.96
male	-0.0059	-0.0006	0.0048	0.43	-0.0199	-0.0103	-0.0006	0.04
age35t45	-0.0112	0.0008	0.0134	0.55	-0.0236	-0.0018	0.0206	0.46
age46t60	-0.0063	0.0055	0.0176	0.79	-0.0037	0.0177	0.0392	0.91
over60	-0.0023	0.0101	0.0224	0.91	-0.0001	0.0216	0.0443	0.94
hhsize	-0.0019	0.0005	0.0029	0.63	-0.0040	0.0003	0.0046	0.54
college	-0.0042	0.0011	0.0064	0.62	-0.0128	-0.0030	0.0069	0.31
out1t4	-0.0030	0.0034	0.0100	0.80	-0.0125	-0.0008	0.0105	0.46
out4t8	-0.0128	-0.0044	0.0050	0.20	-0.0210	-0.0044	0.0121	0.32
out8t24	-0.0198	-0.0092	0.0018	0.08	-0.0454	-0.0262	-0.0079	0.02
outover24	-0.0177	-0.0043	0.0091	0.28	-0.0435	-0.0195	0.0035	0.09
numoutages	-0.0004	0.0002	0.0008	0.72	-0.0007	0.0005	0.0017	0.76
wholecountry	0.5115	0.6807	0.8456	1.00	0.3175	0.3908	0.4651	1.00
rotation	0.0031	0.0087	0.0144	1.00	-0.0116	-0.0021	0.0075	0.35
10 yr. avg. temps	-0.0317	-0.0153	0.0019	0.04	0.0150	0.0346	0.0533	0.99

Model also includes country fixed effects.
Marginal effects for each variable are calculated for one unit increases from the sample mean, with all other variables fixed at the sample mean.
Quantiles calculated via the Highest Probability Density method.

Also from the marginal effects in table 2.6 we note that the parameters are generally homogeneous between the summer and winter seasons. Only five of the 15 included variables have the sign of the mean of their estimated distribution flip between season, and those that do have a sign change have a substantial portion of their probability mass to both the right and left of zero for at least one season, suggesting that the parameter value is close to zero. The exception is the marginal effect of temperature which is highly season-dependent - being strongly negative in the winter and strongly positive in the summer. This is to be expected since increases in summer temperatures will increase the need for indoor cooling and thus the WTP to avoid a power outage, while increases in winter temperatures will decrease the need for heating and consequently decrease the WTP to avoid a winter outage.

Table 2.7 shows the marginal effects estimates for different measures of temperature that may be relevant to survey responses. These measures are explained in section 2.3.1. Each marginal effect is the result of a separate model estimation where only one temperature measure is included in each model. The exception to this is the model which includes both a degree day variable and the square of this variable to further control for non-linearities in the relationship between temperature and WTP. The first four measures shown in the table are measures of regional temperature calculated from the daily observations of the E-OBS dataset. These measures give similar mean marginal effects ranging from -0.01 to -0.017 (€ per °C) in the winter and 0.035 to 0.032 (€ per °C) in the summer. Given the high level of correlation between these four measures, it is unsurprising that they give similar results. To be consistent with the findings from these four measures of regional temperatures, the marginal effect of degree days should be strongly positive in both summer and winter, since both cooling and heating degree days will increase as temperatures become more extreme. However, we find only a weakly positive marginal effect of degree days with the mean marginal effect being very close to zero in both summer and winter. These results taken together suggest that survey respondents may think of general temperature trends when completing the choice exercise but they may not think specifically about the degree to which they use indoor heating and cooling. Another possibility for the relatively weak results from degree days is that our degree day measure, as with any degree day calculation, assigns arbitrary cutoff and censoring points which may not reflect the true 'switch-on' and 'switch-off' temperatures used by respondents; our degree day calculation is shown in (2.6). Due to the relatively weak relationship between degree days and WTP to avoid a power outage we elect to use the temperature measure "daily avg. over past 10 years" for the imputations of WTP over space and time under global warming scenarios related in the next section. Also, the long-term, averaged-over-time nature of the past 10 year temperature measure is more compatible with predicting future WTP based on long-run climate trends which are similarly averaged over 20 year periods.

The final temperature measure used is the average temperature on the day each respondent took their survey. This measure tests the level of cognitive engagement of our respondents to see if they are influenced by the current conditions, or if they can abstract from current conditions and place themselves in the hypothetical outage scenario. The distribution of the marginal effect of current temperature on summer WTP is essentially centered at zero showing that the response to summer outage scenarios is unaffected by current conditions. The marginal effect on winter WTP is positive, so that respondents who are experiencing warmer climates are willing to pay more to avoid winter power outages. This result could just be coincidental, or it may suggest that respondents who are enjoying temperate climates are particularly averse to being left without heating during the cold time of year.

Table 2.7: Marginal effects of temperature measures

	5% quantile	**mean**	**95% quantile**	**prob>0**
January (winter) coefficients				
Daily avg. over past 10 yrs.	-0.0317	-0.0153	0.0019	0.04
Daily min over past 10 yrs	-0.0353	-0.0171	0.0007	0.04
Daily max over past 10 yrs	-0.0220	-0.0102	0.0033	0.07
Daily avg. previous year	-0.0310	-0.0151	0.0024	0.04
Avg. monthly degree days over past 10 yrs.	-8.07E-05	-1.07E-04	3.06E-04	0.83
degree days squared	-2.24E-06	-5.61E-07	9.39E-07	0.31
Daily avg. on day of survey	-0.0012	0.0501	0.1037	0.94
July (summer) coefficients				
Daily avg. over past 10 yrs.	0.0150	0.0346	0.0533	0.99
Daily min over past 10 yrs	0.0088	0.0316	0.0539	0.96
Daily max over past 10 yrs	0.0212	0.0316	0.0458	1.00
Daily avg. previous year	0.0166	0.0353	0.0547	1.00
Avg. monthly degree days over past 10 yrs.	-1.04E-04	1.53E-04	4.14E-04	0.83
degree days squared	-9.29E-06	-5.08E-06	-8.15E-07	0.02
Daily avg. on day of survey	-0.0748	-0.0028	0.0718	0.48

All estimates come from separate model estimations, except for degree days and degree days squared, which are estimated simultaneously. Marginal effects for each variable are calculated for one unit increases from the sample mean, with all other variables fixed at the sample mean. Quantiles calculated via the Highest Probability Density method.

Using the parameter draws from the model which uses monthly averages from the past ten years as the temperature variable we then calculate the hourly WTP to avoid a power outage (β_{is} in (2.3))by country and season. This is an in-sample calculation which loops over all 10,000 usable draws of each parameter ($\boldsymbol{\alpha}$ and β_i) to calculate $\beta_{is} = (1 + \mathbf{z}_{is}\boldsymbol{\alpha}')\beta_i$ for each of the 21,832 scenario/respondent specific observations for both summer and winter. This results in 10,000 draws from an empirical distribution of β_{is} for each observation. These draws are summarized by country to yield the results in table 2.8, and by outage region, as captured in the variable *wholecountry*, to yield the results in table 2.9.

Table 2.8 illustrates the high level of heterogeneity in WTP to avoid power outages across our sample of 19 European nations. Differences in WTP between nations are in part driven by observed variables, such as income disparities and temperature differences, however unobserved country-level factors also strongly drive differences in WTP. These country-specific factors are accounted for by the country level fixed effects included in our econometric model. For instance, France exhibits exceptionally low WTP, possibly due to the public nature of electricity provision in this nation. Also notable for our application is that mean WTP in the summer is lower than in the winter for every nation in our sample. This reflects the

Table 2.8: Mean WTP to avoid one hour of power outage by country and season in Euros

	Winter		**Summer**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
France	0.59	0.09	-0.19	0.11
Germany	1.81	0.20	0.47	0.11
Italy	1.65	0.20	0.62	0.12
UK	1.35	0.14	0.41	0.08
Austria	1.49	0.20	0.49	0.12
Belgium	1.34	0.14	0.44	0.09
Finland	2.37	0.31	0.75	0.19
Netherlands	1.23	0.14	0.32	0.08
Spain	1.69	0.19	0.72	0.12
Sweden	1.89	0.24	0.53	0.14
Portugal	1.17	0.13	0.45	0.09
Bulgaria	1.52	0.22	0.48	0.12
Czech	1.25	0.18	0.30	0.09
Hungary	1.21	0.22	0.46	0.13
Lithuania	1.16	0.19	0.33	0.09
Poland	1.62	0.23	0.85	0.16
Romania	1.26	0.22	0.56	0.13
Slovakia	1.22	0.19	0.47	0.11
Slovenia	2.25	0.25	1.09	0.16

greater proliferation and importance of heating appliances as opposed to air conditioners in European households. However, the difference between winter and summer WTP is generally smaller for warmer nations, such as Portugal and Romania, which reflects the use of air conditioners in parts of these nations. Our spatial imputation presented in the next section allows us to see the temperature-driven heterogeneity in WTP within each nation.

Table 2.9: Mean WTP to avoid one hour of power outage across Europe by area affected and season

	Whole Country	**Local**
Winter	2.05	0.84
	(0.155)	(0.151)
Summer	0.62	0.38
	(0.081)	(0.076)

Values generated using data from the 19 EU countries in our sample, these nations are shown in table 2.8. Standard deviations given in parentheses.

Table 2.9 presents the aggregate estimates of hourly WTP for our entire sample of 19 EU nations. These estimates vary by scope of the outage, confined to the local area or affecting the whole country, and the season of the outage, ranging from €2.05 - €0.38 per hour. Both occurring in the winter and affecting the entire nation approximately double the hourly welfare losses from power outages currently experienced by European households. The next section shows how this dynamic will shift over time as global warming progresses.

2.4.1 Value of supply security under global warming scenarios

This section relates the methods and results of the imputations of WTP through time and across space within our 19 sample nations based on temperatures. The spatial imputations use 2012 E-OBS temperatures to establish the current, or "baseline" WTP, and then use temperatures predicted under three global warming scenarios from the Hadley CM3 model to show how WTP will be affected by global warming across our 19 sample nations. The Hadley CM3 model output includes predicted air temperatures for the entire globe at a resolution of 2.75° latitude and 3.75° longitude for three twenty-year periods, 2020-2039, 2046-2065, and 2080-2099.[3] These predictions are made based on future climate scenarios (known as SRES scenarios), which are detailed, internally-consistent descriptions of possible futures for global civilization [35]. These scenarios take into account many demographic, and technological factors, however the primary variation between scenarios is driven by two large-scale social trends: environmentalism vs economic development, and global vs. regional markets. In total there are six SRES climate scenarios.

We choose three of these scenarios, A1B, A2 and B1, which cover a wide range of future climate outcomes, and impute WTP across our 19 sample countries for these three scenarios. The differences in measurable outcomes between the three scenarios is shown in table 2.10. Scenario A2 represents the most extreme case of climate change we consider and differs markedly from the other scenarios in terms of the sustained, high rate of population growth. The B1 scenario is the most optimistic climate scenario we consider where lower carbon emissions are a result of environmental trends towards renewable energy sources. Finally, the A1B scenario portrays a bustling global economy which is fueled by a balanced mix of fossil and non-fossil energy sources and yields climate outcomes which fall between the A2 and B1 scenarios in terms of the severity of predicted climate change. We choose these three scenarios so that future temperature predictions cover a range of possible outcomes. The imputation method used here can also accommodate the output of different climate models, or different climate scenarios and thus the choice of using the A1B, A2 and B1 scenarios and

[3]These data are available from the IPCC and were used in the IPCC 4th Assessment Report.

the HADCM3 model is by no means the only valid choice for this analysis.

Table 2.10: Comparison of the future climate scenarios used in our study

Scenario	Global Population (billions)	Global GDP ($10^{1}2$ USD)	Income per capita	CO2 Concentration (ppm)	Global Temp. Change (deg. Celcius)
Year 2050:					
A1B	8.7	181	2.8	536	1.6
A2	11.3	82	6.6	536	1.4
B1	8.7	136	3.6	491	1.2
Year 2100:					
A1B	7.1	529	1.6	711	2.9
A2	15.2	243	4.2	857	3.8
B1	7	328	1.8	538	2

From Task Group on Data and Scenario Support for Impact and Climate Assessment [73]

We calculate the predicted change in air temperature for July and January across all of Europe using the 2020-2039 Hadley CM3 model output as the baseline. This yields region-specific predictions of temperature change for three scenarios and *vis a vis* two future time periods, 2046-2065 and 2080-2099. We then add these predictions to the 2012 temperatures from the E-OBS gridded dataset to create predictions of future temperature at 0.25° lat-long spatial resolution. This method allows for spatially-specific predictions of future temperatures while allowing for the use of consistent and readily available climate predictions from a single global model.[4]

As a starting point for the imputation we assign to each E-OBS grid point the mean hourly WTP, from table 2.8, of the nation within which that grid point falls. Again this mean is averaged across all scenario and respondent characteristics including temperatures. We then adjust this WTP based on the difference between the temperature at the individual E-OBS grid point and the mean of the nation-specific observed temperatures in our sample of respondents. This is done by multiplying this temperature difference by the season-specific marginal effect of temperature on hourly WTP, from table 2.6, for each of the 10,000 draws of the marginal effects.

We have thus imputed WTP for each of the 8,173 E-OBS grid points that fall within our sample of 19 countries. Again, the grid point specific WTP only differs from the country mean WTP due to temperature differences between the country mean temperature and the

[4]This method may also slightly underestimate the predicted temperature increase since the temperature increase between 2012 and 2020 is not added in. However, the predicted increase during this period is relatively small compared to the increases predicted by the end of the century.

temperature at that grid point. Figure 2.4 shows the average hourly WTP across our 19 sample nations based on 2012 temperatures. Notice that summer WTP is lower than winter WTP for the entire sample region. Adjusting this image of current WTP based on predicted temperature increases and the marginal effects of temperature in both June and July yields figures 2.5 - 2.10, which show predicted hourly WTP for time periods 2046-2065 and 2080-2099 for each of the three SRES climate scenarios. Notice that in the more extreme warming scenarios, A1B and A2, the gap between summer and winter WTP begins to close, especially in the areas of Central and Southern Europe along the Mediterranean climate zone, such as parts of Spain, Bulgaria, Romania, and Italy, where climates are generally warmer.

As a second imputation technique we can predict WTP of our sample of respondents through time based on changes in temperatures. This imputation adjusts the 10,000 draws of β_{is}, the respondent/scenario specific estimate of hourly WTP from (2.3), based on predicted temperature change and the draws of the marginal effects of temperature. The temperature change is calculated in the same manner as for the spatial imputations using temperature estimates from the Hadley CM3 model under the SRES A1B scenario. This scenario falls in the middle in terms of the severity of future climate change and thus serves as a good illustrative case of WTP in the future. We multiply the predicted temperature change by the marginal effect draw and add this value to the draw of β_{is}. Looping this procedure over the 10,000 draws of β_{is} and of the marginal effects allows estimation uncertainty to carry through from the initial WTP estimation and also from the projection of the effect of temperature changes on WTP. This results in the relatively large predictive standard deviation on the future WTP estimates which are shown in tables 2.11 and 2.12 along with mean WTP by nation, season and outage scope. These results are directly comparable to those in tables 2.8 and 2.9 which represent the current levels of WTP.

The future predictions of WTP amongst our sample of respondents shows that as Europe warms summer and winter WTP will begin to converge. However, By 2080-2099 winter WTP will still be larger than summer WTP across Europe. Since the marginal effects of temperature on WTP are larger in magnitude in the summer than in the winter we find that winter WTP will decrease slower than summer WTP will increase. Consequently, hourly WTP, averaged over seasons, will increase across Europe as a result of global warming by about €0.02 per household by 2055, and by about €0.04 by 2089. This implies that, on average, per household hourly welfare losses from blackouts will likewise increase in the future. While the increase in overall WTP due to global warming is small on a per household

Table 2.11: Mean WTP to avoid one hour of power outage by country and season in Euros under climate scenario A1B

	Winter 2055		**Summer 2055**		**Winter 2089**		**Summer 2089**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
France	0.55	0.94	0.00	0.85	0.52	0.94	0.00	0.85
Germany	1.77	1.16	0.53	0.78	1.74	1.16	0.60	0.78
Italy	1.61	1.08	0.70	0.86	1.57	1.09	0.77	0.86
UK	1.33	0.96	0.46	0.76	1.31	0.96	0.50	0.76
Austria	1.45	1.03	0.56	0.78	1.42	1.03	0.63	0.78
Belgium	1.30	1.05	0.50	0.94	1.28	1.06	0.56	0.94
Finland	2.33	1.32	0.80	0.85	2.30	1.33	0.87	0.86
Netherlands	1.21	0.95	0.36	0.70	1.18	0.96	0.42	0.70
Spain	1.66	1.09	0.78	1.01	1.64	1.09	0.83	1.01
Sweden	1.86	1.30	0.58	0.94	1.83	1.31	0.65	0.94
Portugal	1.14	0.83	0.52	0.75	1.11	0.83	0.57	0.75
Bulgaria	1.49	1.11	0.54	0.89	1.45	1.11	0.62	0.89
Czech	1.12	1.02	0.36	0.79	1.19	1.03	0.43	0.79
Hungary	1.17	0.89	0.53	0.75	1.13	0.90	0.61	0.75
Lithuania	1.14	0.91	0.38	0.71	1.09	0.91	0.48	0.72
Poland	1.59	0.97	0.90	0.88	1.55	0.97	0.98	0.88
Romania	1.22	1.04	0.62	1.03	1.18	1.04	0.71	1.03
Slovakia	1.18	0.94	0.54	0.88	1.14	0.95	0.62	0.88
Slovenia	2.21	1.25	1.17	1.14	2.17	1.26	1.24	1.14

Negative estimates were censored at 0.
Period 2046-2065 is referenced as year 2055 and period 2080-2099 is referenced as 2089.

Table 2.12: Mean WTP to avoid one hour of power outage across Europe by area affected and season under climate scenario A1B

	2055		**2089**	
	Whole Country	**Local**	**Whole Country**	**Local**
Winter	2.02	0.81	1.99	0.78
	(1.385)	(0.681)	(1.388)	(0.687)
Summer	0.68	0.44	0.75	0.51
	(1.000)	(0.713)	(1.003)	(0.716)

Values generated using data from the 19 EU countries in our sample, these nations are shown in table 2.8. Period 2046-2065 is referenced as year 2055 and period 2080-2099 is referenced as 2089.

basis, when aggregated over millions of residents potentially affected by blackouts these changes can translate into large increases in the total welfare losses from a give power outage.

It should be noted that, as with any future prediction, our hourly WTP imputations rely on the assumption that the use and importance of electricity in the European household remain static in all ways aside from increases or decreases in the usage of apparatus related to temperature (e.g climate control, refrigeration). Furthermore, societal changes such as economic development, urbanization, and energy market structure can also impact household

WTP to avoid a power outage. The possibility of such changes are not explicitly considered in our analysis.

Figure 2.4: Current hourly WTP to avoid power outages across our 19 sample nations

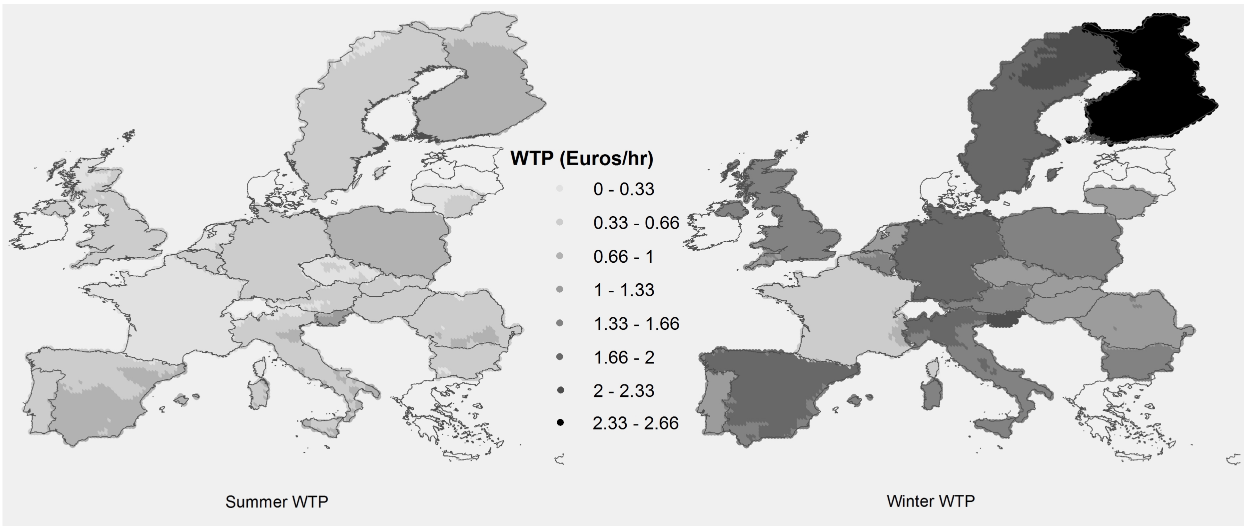


Figure 2.5: Predicted hourly WTP to avoid power outages 2046-2065 under climate scenario A1B

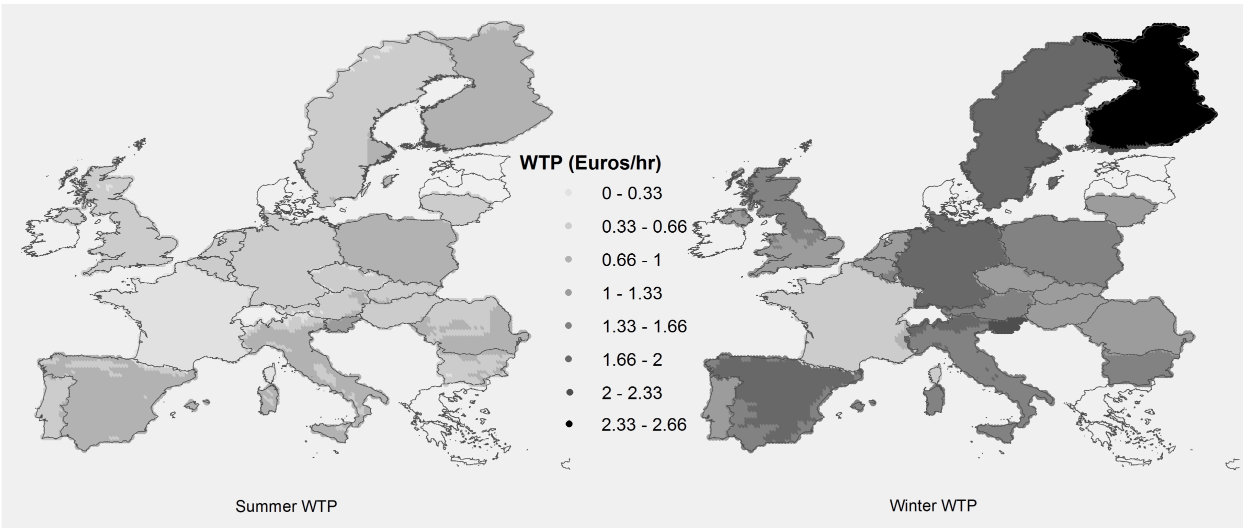


Figure 2.6: Predicted hourly WTP to avoid power outages 2080-2099 under climate scenario A1B

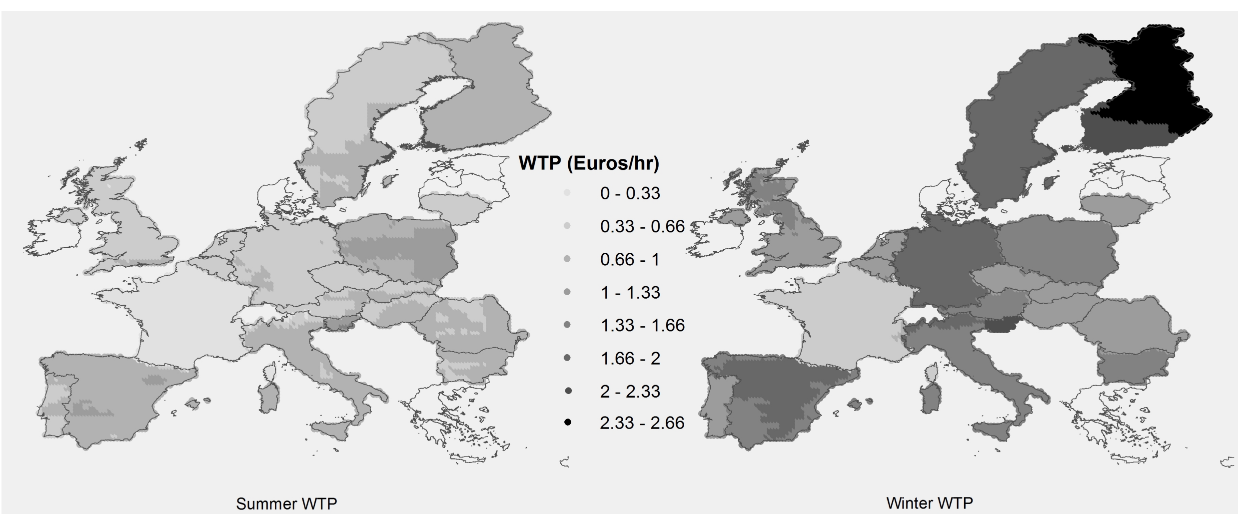


Figure 2.7: Predicted hourly WTP to avoid power outages 2046-2065 under climate scenario A2

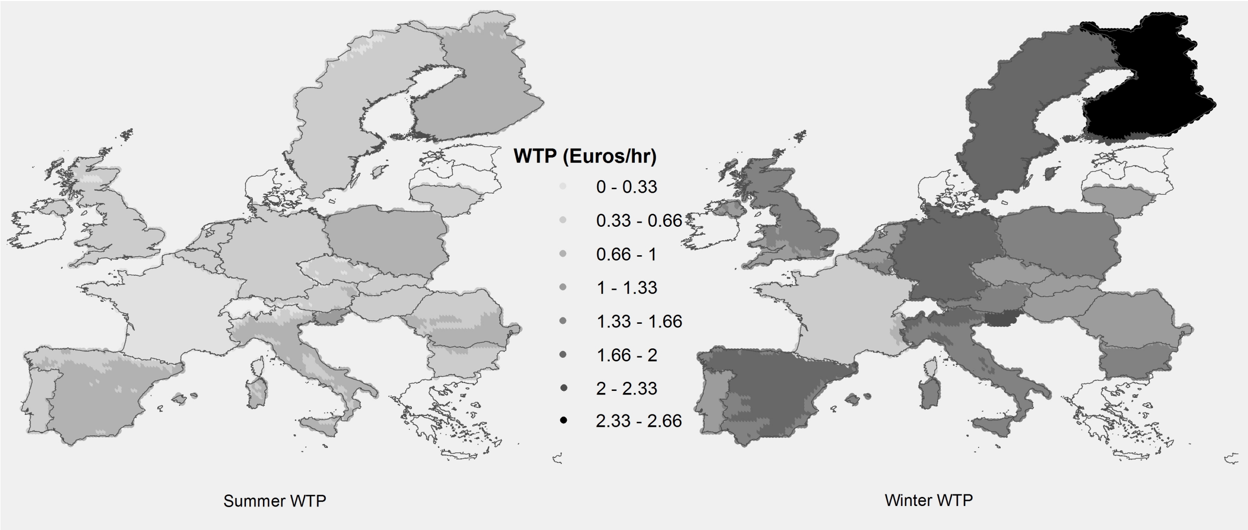


Figure 2.8: Predicted hourly WTP to avoid power outages 2080-2099 under climate scenario A2

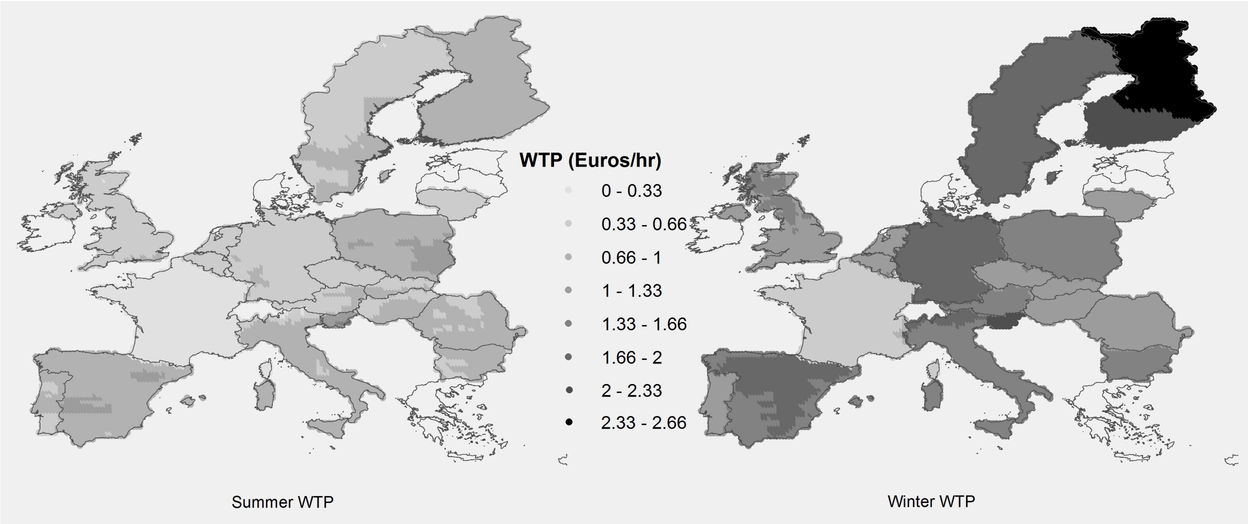


Figure 2.9: Predicted hourly WTP to avoid power outages 2046-2065 under climate scenario B1

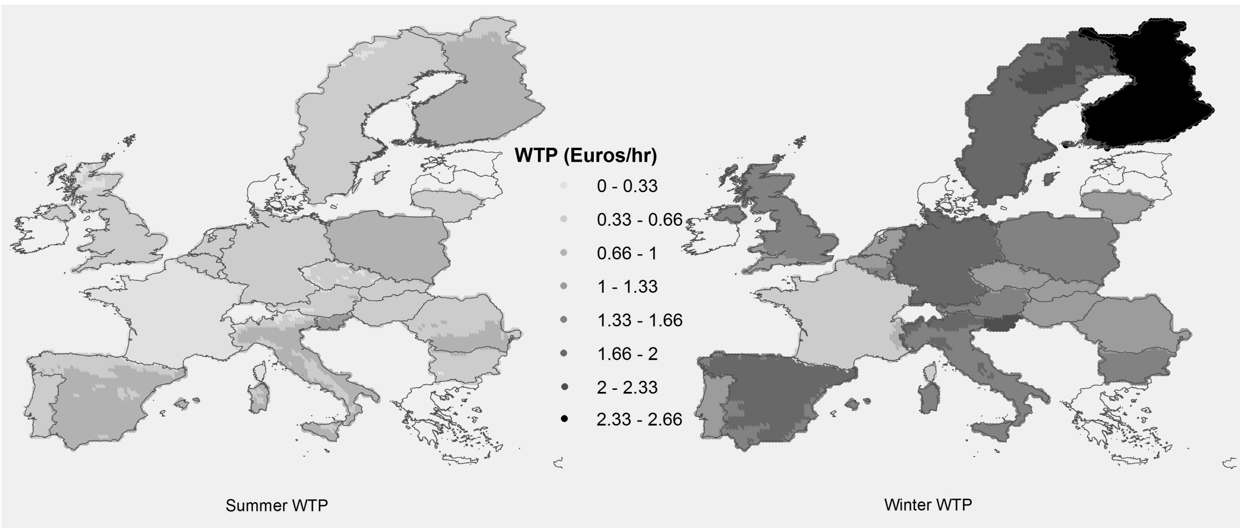
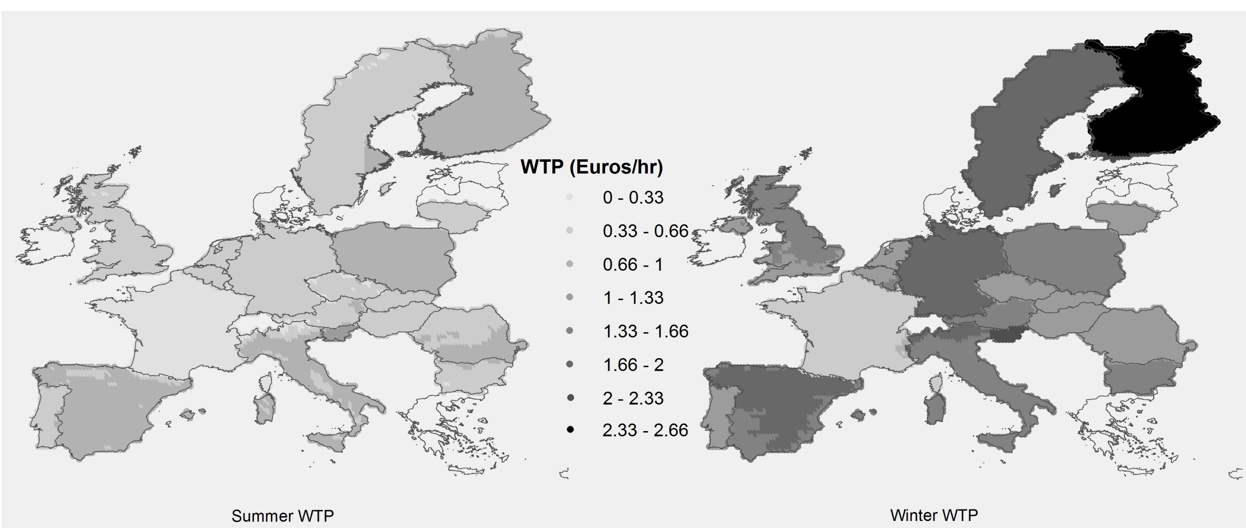


Figure 2.10: Predicted hourly WTP to avoid power outages 2080-2099 under climate scenario B1



2.5 Conclusion

As the EU continues to invest in a renewable energy grid, planning this grid to ensure the socially optimal level of supply security requires knowledge of the welfare losses from power outages. While other studies have estimated these outage costs for some European countries, we present a methodologically consistent estimate of the WTP to avoid power outages across 19 EU nations. Our estimates of current WTP show strong heterogeneity by country, season and scope of the outage, with WTP to avoid a power outage in the winter being consistently higher than WTP to avoid a summer outage. By linking responses from a choice experiment designed to elicit WTP to temperature measures from the area where respondents live, we are able to estimate the effect that local temperatures have on the WTP to avoid a blackout. The results show that increases in temperatures in the summer will increase WTP, while increases in winter temperatures will decrease WTP. This is to be expected given the observed relationship between temperature and energy usage which is driven in a large part by the use of energy-intensive heating and cooling apparatus.

Since much of the electricity infrastructure require long-term investment and planning it would be preferable to also assess how welfare losses from power outages will change in the future. As temperatures are shown to be strong drivers of WTP, and since temperatures are expected to increase due to global warming, it is likely that the the magnitude and spatial distribution of welfare loss from power outages will change as temperatures increase. Furthermore, global warming is predicted to make extreme weather events that often damage electricity grids more frequent, making the provision of supply security in the future potentially more difficult [36, ch. 10]. As a first look at future welfare losses from power outages we predict future WTP to avoid an outage based on temperature projections from the Hadley CM3 climate model. These imputations over time are completed both across the spatial area of our sample, and for our sample of survey respondents. The results for the spatial imputation show that hourly per household welfare losses from summer outages will increase while losses from winter outages will decrease across Europe. These spatial imputations can also be used to inform regional grid development. The prediction of in-sample WTP under a future climate scenario shows that the difference between summer and winter WTP is likely to shrink over the next century in Europe. For grid development this result suggests that more emphasis should be put on securing the grid from summertime outage causes, such as heatwaves. Furthermore, the results suggest that overall hourly WTP across our sample, averaged across seasons, will increase as the climate warms, suggesting that the importance of supply security to the European household will increase as a result of climate change.

Chapter 3

Visitor time use at Lake Tahoe as the climate warms

3.1 Introduction

While economic literature on the effects of climate change on general time allocation is slowly emerging, to date little is known of how increased temperatures might affect consumers' choice of recreational activities in a specific area. Our study aims to fill this gap, and to provide Lake Tahoe managers with an understanding of the behavioral changes that will likely result from climate change induced temperature increases. To do so we use data from a survey of Tahoe Basin visitors completed at various sites around the lake throughout the summer of 2004. These are particularly rich "diary" data which catalog the activities chosen by each member of the household hourly from 8 am until 9 pm. We estimate regression models which relate the proportion of time allocated to each category of activities to household characteristics and temperatures. The hypothesis tested is that temperature is a significant driver of visitor recreation choices and time use at Lake Tahoe.

The work of Zivin and Neidell [81] is the first to show that activity choices are sensitive to ambient temperatures. The authors estimate an inverse U-shaped function over temperature for time allocated to outdoor activities for a nation-wide sample. Specifically, they estimate that at the 100°F(37.7°C) threshold increases in temperature begin to decrease the time spent outdoors. In contrast, they predict a U-shaped function over temperature for indoor activities for the typical U.S. household.

Other work in recreation demand has illuminated some of the important factors which drive household time use and recreation decisions. For example, household size and composition, such as the number of small children, will drive activity choice and time use [61, 28]. Related papers have shown that activity choice is the result of a complex interaction between household members and their environment [6, 74]. Other work has shown that the frequency of leisure time has significant impacts on the way such time is allocated [39]. For our study this suggests that visitors who frequent the Tahoe area are likely to allocate their time differently than those who rarely visit the Tahoe area. Furthermore, Paudel et al. [57] showed that visitors' site and activity decisions relating to trips to Louisiana coastal areas are influenced largely by environmental quality, travel distance and the visitor's income.

Previous studies of recreation demand have also used diary data. For instance, Zhang and Fujiwara [80] estimate utility functions for shared and non-shared activities for elderly couples. The authors collect diary data which account for each household member's activities and travel from 6am - 8pm for an entire week. Similarly, Hyeon Joh et al. [34] use diary data from two consecutive days to estimate the utility functions underlying time use decisions. Khandker and Miller [41] also use a form of diary data which tracks both the planning and execution of daily activities; this allows the authors to model the process of activity program generation within the household. To our knowledge, the data employed in our study is the first diary dataset which is specific to the activity choices of visitors to a certain recreation area.

The results of our statistical analysis find that time spent on the beach and pursuing water sports will increase significantly under scenarios of rising temperatures while time spent indoors and staying at accommodations will decrease. This has important policy consequences for resource planners, especially given the environmental and overcrowding difficulties that can arise from high volumes of beach and water users at Lake Tahoe.

3.2 Data

Data for this project come from the 2004 "Tahoe Recreation Frequency and Duration Survey" administered by Chuck Nozicka consulting and a team at University of Nevada Reno (UNR) Resource Economics. The on-site survey given to each group of willing visitors was administered at 35 recreation sites around Lake Tahoe during the months of July and August, when visitor use is heavy. The locations of these sites are shown in figure 3.1. The survey required households to account for each hour of their day starting at 8 am until 9 pm for each person in their party. The survey included a wide range of common recreation activities to choose from, as shown in figure 3.2, as well as collecting demographic and socioeconomic information from each group.

Figure 3.1: Locations of visitor survey sites around Lake Tahoe

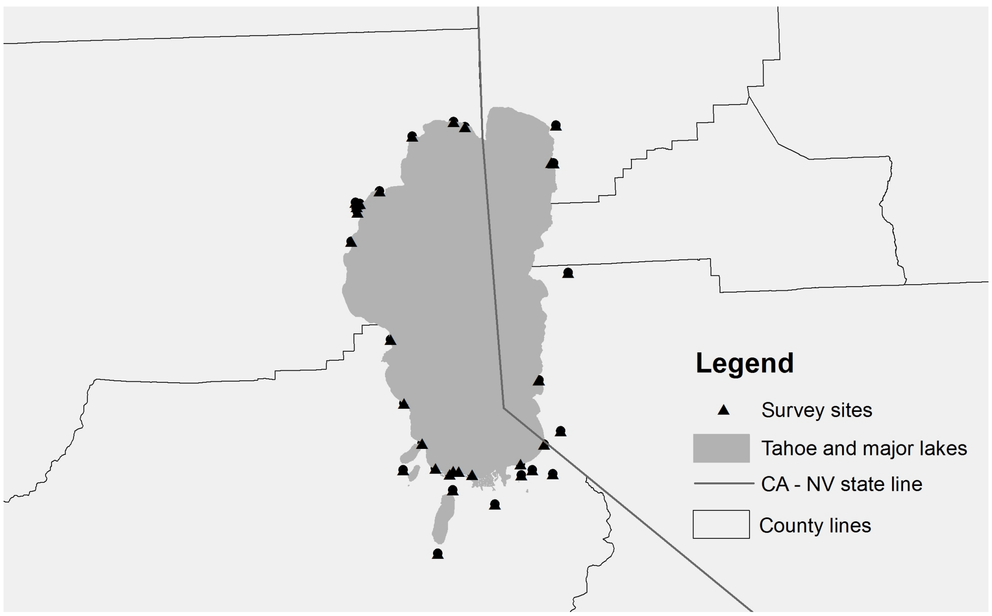


Figure 3.2: Example of visitor time use survey

OUTDOOR SPORTS	Today, our party participated / will participate in	NUMBER OF PARTICIPANTS PER ACTIVITY AND HOUR													
		morning				afternoon					evening				
		8-9	9-10	10-11	11-12	12-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	after 9
Walking															
Trail Hiking	✓		3	3	3										
Backpacking															
Bike (mountain)															
Beach Activities (swim, games, relax)	✓		3	3	3	6	6	6	6						

EXAMPLE

The survey was administered by teams from UNR, with each team visiting at least two survey sites per day with at least an hour spent at each site. The sampled respondents were those who were approached by the survey teams and were willing to participate in the survey. Small prizes were offered to respondents who completed the survey to incentivize participation. While the survey administration required considerable effort, it is still possible that the sampling mechanism did not yield random sample of Tahoe visitors. We compare our survey data to the data procured from a Lake Tahoe Visitors Authority survey of South Lake Tahoe visitors completed in the summer of 2015 to assess the relevance of our sample to the current tourism situation at Tahoe [69]. The comparison of household demographics between the surveys is given in table 3.1, and shows that households are very similar in their age, income, size, and the percent that have children. However, there is a relatively large disparity between surveys in the percentage of first time visitors, with our 2004 survey showing a much lower proportion of new visitors to the Tahoe area. This could be due to an under-representation of first time visitors in our survey, or to changing visitor trends over time with more new visitors now coming to the area. In either case, the lower percentage of first time visitors in our sample will be considered when interpreting the results of this study.

Table 3.1: Comparison of household demographics

Metric	Our Data	Comparable Survey
Year	Summer 2004	Summer 2015
Childless households	53%	44%
Mean Age	43	42
Mean Income ($2015)	$118,000	$136,000
First Time Visitors	16%	32%
Mean Household Size	2.8	3

For details of comparative survey see SMG Consulting [69]. Summary of 2004 survey uses all 544 respondents.

To allow for sufficient sample sizes for each activity type specific activities were aggregated into activity categories. This yields six categories of activities and one "residual category" which accounts for visitors who are taking part in an activity that was not specified in the survey, or visitors that stayed in their accommodation for part of the day.

Category 1 - land sports (e.g. walking, jogging and biking)

Category 2 - beach activities

Category 3 - water sports (boating, snorkeling and fishing)

Category 4 - field sports (golf, soccer, etc.)

Category 5 - outdoor leisure (sightseeing, picnicking, etc.)

Category 6 - indoor leisure (e.g. shopping, gaming and dining)

Residual Category - stay at accommodation/other activities

Based on these categories we computed household shares - the percent of the total available person hours the household allocated to a category of activities on the interview day. Of the 544 observations initially collected in the field, we used only those that represented full-day visitors, i.e. multi-day visitors that were not interviewed on an arrival or departure day, so that we can account for the entire day of activities for each household in our sample. This left a sample of 227 households for which we recorded participation shares for each of three time segments: morning (8am-12pm), afternoon (12pm-4pm), and evening (4pm-9pm). Thus, we have $227 \times 3 = 681$ observations per activity category and three observations per household. All respondents in our sample can be classified as 'visitors to the Tahoe area,' since their primary residences are not in Tahoe. Time use for each activity category is summarized in table 3.2, showing that category 2, 5 and 1 activities are the most popular during the summer months at Lake Tahoe. The final column of table 3.2 shows the percentage of households that did not participate in each activity category during a time segment. For category 3 and 4 activities these percentages are especially high, which implies that there are many instances of zero time shares of these activity types.

Table 3.2: Average proportion of the day spent on each activity category

	Mean	**Std. Dev.**	**Min**	**Max**	**Pct. Non-participation**
Category 1 Share	0.105	0.181	0	1	0.639
Category 2 Share	0.172	0.270	0	1	0.606
Category 3 Share	0.029	0.101	0	1	0.890
Category 4 Share	0.009	0.058	0	0.75	0.968
Category 5 Share	0.131	0.228	0	1	0.649
Category 6 Share	0.062	0.145	0	1	0.771

The sum of the means implies that 49% of visitors' time was spend on residual category activities, mostly staying at their accommodation.

Observations were collected on different days and at different sites around the Lake Tahoe area, with the same site being visited multiple times throughout the survey period. The number of observations by survey site is given in table 3.3. The site names shown in the table and the varied survey locations shown in figure 3.1, suggest that different survey locations may predispose visitors to certain activities, for instance visiting a beach area is likely to involve some sort of beach activity. Thus, site specific effects must be accounted for in our statistical approach.

Table 3.3: Observations by survey site

Site Name	**Number of Households Surveyed**	**Percent of Sample**
Kings Beach	36	5.29
North Tahoe Beach Center	12	1.76
Carnellian Bay	12	1.76
Commons Beach	36	5.29
Rafting Truckee	12	1.76
Tahoe City Golf Course	3	0.44
Zephyr Cove	66	9.69
Memorial Point	9	1.32
Sand Harbor	66	9.69
Spooner Trailhead	6	0.88
Kahle Park	3	0.44
South L. Tahoe Rec Center	9	1.32
El Dorado Beach	27	3.96
Bijou Golf Course	24	3.52
Camp Richardson	45	6.61
Emerald Bay	48	7.05
Cascade trailhead	21	3.08
Tallac visitor center	30	4.41
Glen Alpine trail	21	3.08
Tallac beach / Kiva beach	12	1.76
Gondola Tower SLT	15	2.2
Pope beach	42	6.17
Bladwin Beach	18	2.64
Fallen Leaf Lake Campground	21	3.08
Sugar Pine State Park	33	4.85
DL Bliss State Park	54	7.93
Total	681	100

The other data necessary for this analysis are weather data for the Lake Tahoe area from the summer of 2004. These data are available courtesy of the National Climactic Data Center. Hourly temperatures were reported by the South Lake Tahoe Airport weather station. These temperatures were averaged across our three time periods of interest: morning (8am-12pm), afternoon (12pm-4pm), and evening (4pm-9pm). Temperatures were then matched to survey respondents based on the day each respondent took the survey. A summary of these temperature data is given in table 3.4. As can be seen in the table, the average temperature of the afternoon period is significantly higher than the average of morning or evening temperatures, which makes it possible for households to optimize their daily activities based on temperature changes. Precipitation, which would likely drive visitors indoors, is not an issue for our sample, since none of the survey days had any rainfall as measured by the South

Lake Tahoe Airport weather station.

Table 3.4: Summary of temperature data by time segment

	Average Temperature°C	**Std. Dev.**	**Min**	**Max**
Morning (8am - 12pm)	22.30	1.23	19.67	23.78
Afternoon (12pm - 4pm)	25.47	1.39	22.44	27.67
Evening (4pm - 8pm)	22.14	1.57	19.33	24.44

3.3 Methods

Our primary aim is to estimate the relationship between temperature and visitors' recreation choices at Lake Tahoe. The dependent variable is the share of available time each household spent on a particular category of activities during each of the three time segments. Total time is equal to the number of persons in the household multiplied by the total time accounted for by the survey (8am - 9pm) - a household with three persons thus has $3 \times 13 = 39$ hours to allocate throughout the day. While we could also model participation rates, the percent of households that participated in a certain category of activities in a give time frame, as the dependent variable, difficulties with estimating participation rates for certain activities have been discussed at length in the recreation demand literature [25]. The rich data structure afforded by our diary data, which accounts for every hour of the day for every member of each household, allows us to circumvent this problem and model the proportion of man-hours spent on an activity instead of participation rates.

Thus, we have six different regression equations, one per activity category, that relate the share of man-hours spent on that category of activities by a given household to the relevant average temperature for each time segment and other explanatory variables. Another option would be to consider these six equations as a systems and estimate the coefficients via the Seemingly Unrelated Regression (SUR) technique [79]. However, since the set of explanatory variables for each equation is the same, efficiency gains from SUR will be negligible, as shown by Zellner [79]. Furthermore, our chosen method of equation by equation estimation will give consistent results, assuming we have no endogeneity problems, and allows for greater flexibility in specifying hierarchical random effect structures specific to each equation.

The explanatory variables are summarized and defined in table 3.5. These variables are chosen based on the results of previous research. Past literature has shown that activity choice varies with visitation length [49]. Thus, we include the variables "*visit length*" and "*vac share*" in the model. The variable "*kids*" accounts for the effects of family composition, which have been shown to drive time use and activity choices [61, 28]. As visitation frequency has been shown to also drive choices we include the indicator variable "*first visit*" to account for the differences between first time and repeat visitors to the Tahoe area [39]. Finally, the inclusion of "*income*"[1] accounts for financial differences between households which have been shown to be important in the context of recreation demand [57].

Table 3.5: Explanatory variables included in regression equations

Variable	**Description**	**Mean**	**Std. Dev.**	**Min**	**Median**	**Max**
avgtemp	Avg. air temperature	23.3	2.1	19.3	23.4	27.7
kids	Number of people under age 18 in household	1.0	1.2	0.0	0.0	5.0
first visit	Indicator for first time visitors to Tahoe	0.1	0.4	0.0	0.0	1.0
visit length	Number of days visiting Tahoe area	8.1	9.0	3.0	6.0	85.0
vac share	Pct. of vacation that has passed	0.6	0.2	0.1	0.7	0.9
income	Household income in $000's	113.7	64.0	20.0	87.5	250.0

Regressions also include a constant term, and random effects at the household level. Some regressions include fixed or random effects at the survey site level when necessary as shown in table 3.6.

To obtain an unbiased estimate of the effect of temperature on activity choice we must control for potential sources of confounding factors. As a primary source of confounding factors we have selection bias which results from interviewing households at particular survey sites. Since certain activities are only available at certain sites and since some sites 'specialize' in a group of activities, we are more likely to observe these activities at these sites, e.g. beach activities at a beach. This would confound our estimate of the effect of temperature on activity choice if the temperature variable (*avgtemp*) happens to be correlated with survey site selection, e.g. surveys at beaches occurred on hotter days. The second source of confounding factors are household specific effects. Past research has shown that household-specific factors such as past experience, daily routine, and exposure to marketing can influence recreation choices [52, 15]. Since each household was interviewed at only one survey site these confounding effects have a hierarchical structure, whereby survey site may effect the households surveyed and also the activities chosen by these households, while household-level effects

[1]Respondents were asked to self-report their income by choosing one of 9 income categories from 'under 20,000' to 'over 200,000'. The *income* variable reflects the median value of the respondent's chosen income category with 15,000 used for those who chose 'under 20,000' and 250,000 used for those who chose 'over 200,000'.

may influence the household's activity choice.

In order to account for these nested sources of confounding factors we employ hierarchical mixed models to analyze our data which use a combination of fixed and random effects. We elect to control for household level effects by including a suite of household level covariates in the regression equations and allowing for random effects at the household level. With only three observations per household, the use of household level fixed effects would greatly diminish the degrees of freedom in the model and would rely on variation between morning, afternoon and night temperatures to identify the effect of temperature on activity choices. This leads to the separate, potentially confounding issue of activity ordering. It is well recognized in the recreation demand literature that sequences of activities are related and that the order of activities is relevant to activity choice [10]. If we rely purely on within-household variation to estimate the relationship between temperature and activity choice this estimate may be confounded by ordering effects which are correlated with temperatures. For example, if beach activities are often planned to follow land sports, then going to the beach is likely to take place during hotter parts of the day than playing land sports, which would amount to a spurious correlation between beach activity and temperature increases. With no way to adequately account for these ordering effects in this context we instead use household level random effects and a suite of household level variables to account for heterogeneity at the household level. This allows the model estimation to take advantage of the rich inter-household variation in temperature data which results from surveys being conducted on many different days throughout the summer of 2004, and thus is not subject to ordering effects.

To control for the potential confounding effect of selection bias by survey sites we test if either fixed effects, or random effects at the site level are necessary. The choice between random and fixed effects is driven by a conventional Hausman test comparing a random effects model to a fixed effects model. If the Hausman test fails to reject the null this suggests that the random effects model is consistent. In this case we then test for the inclusion of random effects at the site level via a standard Lagrange Multiplier test. A summary of these statistical tests is given in table 3.6. As can be seen in the table, we find that fixed effects at the survey site level are necessary for category 2 and 5 activity share regressions. Categories 1, 3 and 4 activity share regressions require random effects, whereas the category 6 equation requires neither fixed nor random effects at the survey site level.

The regression model for a single activity share equation of share w_{ijk} from observation i of

Table 3.6: Statistical tests for the inclusion of site-level fixed and random effects

	Hausman Statistic	p - value	Reject?	LM Statistic	p - value	Reject?	Included Effect
Category 1 Eq.	4.57	0.6	no	20.4	0	yes	RE
Category 2 Eq.	38.8	0	yes	104	0	yes	FE
Category 3 Eq.	2.79	0.83	no	10.5	0	yes	RE
Category 4 Eq.	11.17	0.068	no	31.5	0	yes	RE
Category 5 Eq.	13.93	0.03	yes	19.66	0	yes	FE
Category 6 Eq.	8.89	0.18	no	0.83	0.1816	no	none

Hypothesis tests evaluated at the 5% level of significance.
All regressions allow for household-level random effects.

household j at site k is specified below

$$\begin{aligned} w_{ijk} &= \beta_0 + \boldsymbol{\beta}\mathbf{X}_{ijk} + \nu_k + u_j + \epsilon_{ijk} \\ \epsilon_{ijk} &\sim N(0, \sigma^2) \quad u_j \sim N(0, e_j^2) \end{aligned} \tag{3.1}$$

with random effects u_j at the household level. The site level term ν_k, can be either a site specific fixed effect or a random effect[2]. See table 3.6 for the specification of ν_k in each of the six activity category share equations[3]. We estimate six separate share equations via the restricted maximum likelihood technique, where w_{ijk} is the share of person-hours for the day spent on one of the six activity categories; the dependent variables are summarized in table 3.2.

Upon estimating the parameters of the six regressions, we impute predicted shares of the day that would be spent on each category of activities for each household. To then predict how the proportion of time spent on each category of activities will change with global warming we increase the observed temperatures based on predictions of temperature increases in the Tahoe area from climatology models. A climate change impacts report for Lake Tahoe was completed in 2010 (see Coats et al. [23]) and included regional air temperature increases under climate scenarios A2 and B1 from the GFDL climate model. The A2 scenario depicts a globalized world with high population growth, and consequently leads to larger increases in temperature over the 21st century than the B1 scenario, which depicts a future of renewable energy integration [35]. We use the downscaled, or regionalized, climate predictions for the Tahoe area from Coats et al. [23], which predict a medium-term (by 2050) temperature increase of about 1°C under B1, and about 1.5°C under A2, and a long-term (by 2100)

[2] If ν_k is a random effect then $\nu_k \sim N(0, e_k^2)$.
[3] Note that $\nu_k = 0 \quad \forall k$ in the category 6 share equation.

temperature increase of about 2.5°C under B1, and about 4°C under A2.

To impute activity shares under warming climates we multiply the estimated coefficient on average temperature from each of our six activity category regressions by these predicted increases in temperature. This gives a predicted share of each of the six activities for each household under each of the global warming scenarios and time horizons. Even with a 4°C increase in temperatures, as predicted under the A2 climate scenario by 2100, the mean and maximum daily temperatures observed in our data will still fall below the 100°F(37.7°C) threshold where outdoor leisure time begins to decrease, as found by Zivin and Neidell [81]. Thus, across the range of temperatures we are considering these linear predictions should be good approximations of the change in activity choices as temperatures increase. The household specific imputations are averaged to present the predicted mean activity shares for Lake Tahoe visitors currently and under climate change scenarios.

3.4 Results

The model coefficient estimates and standard errors are reported in Table 3.7. The results indicate that temperature significantly influences a household's recreation choices for activity categories 2 (beach), 3 (water sports) and 6 (indoor leisure). The coefficient estimates for average temperature in categories 2 and 3 are both positive, indicating that higher summer temperatures lead to increases in time spent at the beach and engaging in outdoor water sports, such as boating. The coefficient estimate for category 6 is negative indicating that as temperature rises households spend less time at indoor leisure. This is consistent with the results of Zivin and Neidell [81], who found that warmer temperatures will lead to increased time spent outdoors for the range of temperatures below 100°F(37.7°C). The coefficient estimates for average temperature in categories 1 (land sports), 4 (field sports) and 5 (outdoor leisure) are all negative, but not statistically significant at the 5% level. This is likely due to the fact that time spent on activities which are captured in our residual category, such as staying in and "doing nothing," decrease as temperature rises. Thus, the increase in beach and water sport time is largely offset by a decrease in time spent on indoor leisure and staying in their accommodation, and by a small decrease in time spent playing outdoor sports.

The only other household level explanatory variable which shows statistical significance is *kids* - the number of persons under 18 in the household. Households with more young persons spend more time in category 2 (beach) activities. The indicator variable for first time visitors (*first visit*) is not statistically significant in any of the regressions, and thus the potential under-representation of first time visitors in our sample (shown in table 3.1) should not be biasing the results.

Table 3.7: Estimated coefficients from the six activity share OLS regressions

	Category 1 - Land Sports					**Category 2 - Beach**				
	Coef.	**Std. Err.**	**Z Stat.**	**Prob**$>Z$		**Coef.**	**Std. Err.**	**Z Stat.**	**Prob**$>Z$	
avgtemp	-0.0014	0.0035	-0.4	0.69		0.0524	0.0049	10.7	0.00	***
kids	-0.0077	0.0060	-1.3	0.20		0.0149	0.0088	1.7	0.09	*
first visit	0.0171	0.0209	0.8	0.41		0.0265	0.0309	0.9	0.39	
visit length	-0.0003	0.0009	-0.3	0.74		-0.0010	0.0013	-0.8	0.43	
vac share	-0.0070	0.0429	-0.2	0.87		-0.0142	0.0651	-0.2	0.83	
income	-3.5E-07	1.2E-04	0.0	1.00		-6.7E-05	1.8E-04	-0.4	0.70	
constant	0.1559	0.0893	1.8	0.08	*	-0.9912	0.1288	-7.7	0.00	***
	Category 3 - Water Sports					**Category 4 - Field Sports**				
	Coef.	**Std. Err.**	**Z Stat.**	**Prob**$>Z$		**Coef.**	**Std. Err.**	**Z Stat.**	**Prob**$>Z$	
avgtemp	0.0062	0.0019	3.3	0.00	***	-0.0021	0.0011	-1.9	0.06	*
kids	-0.0005	0.0035	-0.2	0.88		-0.0018	0.0018	-1.0	0.31	
first visit	-0.0012	0.0122	-0.1	0.92		-0.0067	0.0063	-1.1	0.29	
visit length	0.0005	0.0005	1.0	0.31		-0.0001	0.0003	-0.2	0.82	
vac share	-0.0349	0.0253	-1.4	0.17		0.0009	0.0131	0.1	0.94	
income	5.4E-05	6.8E-05	0.8	0.42		3.7E-05	3.5E-05	1.0	0.30	
constant	-0.1043	0.0495	-2.1	0.04	**	0.0603	0.0286	2.1	0.04	**
	Category 5 - Outdoor Leisure					**Category 6 - Indoor Leisure**				
	Coef.	**Std. Err.**	**Z Stat.**	**Prob**$>Z$		**Coef.**	**Std. Err.**	**Z Stat.**	**Prob**$>Z$	
avgtemp	0.0076	0.0040	1.9	0.06	*	-0.0079	0.0027	-3.0	0.00	***
kids	-0.0098	0.0099	-1.0	0.32		-0.0055	0.0046	-1.2	0.23	
first visit	-0.0144	0.0346	-0.4	0.68		-0.0178	0.0159	-1.1	0.26	
visit length	0.0001	0.0014	0.1	0.93		-0.0009	0.0007	-1.4	0.15	
vac share	-0.0328	0.0728	-0.5	0.65		0.0406	0.0320	1.3	0.21	
income	-4.1E-06	2.0E-04	0.0	0.98		-2.7E-05	8.8E-05	-0.3	0.76	
constant	0.0485	0.1130	0.4	0.67		0.2416	0.0680	3.6	0.00	***

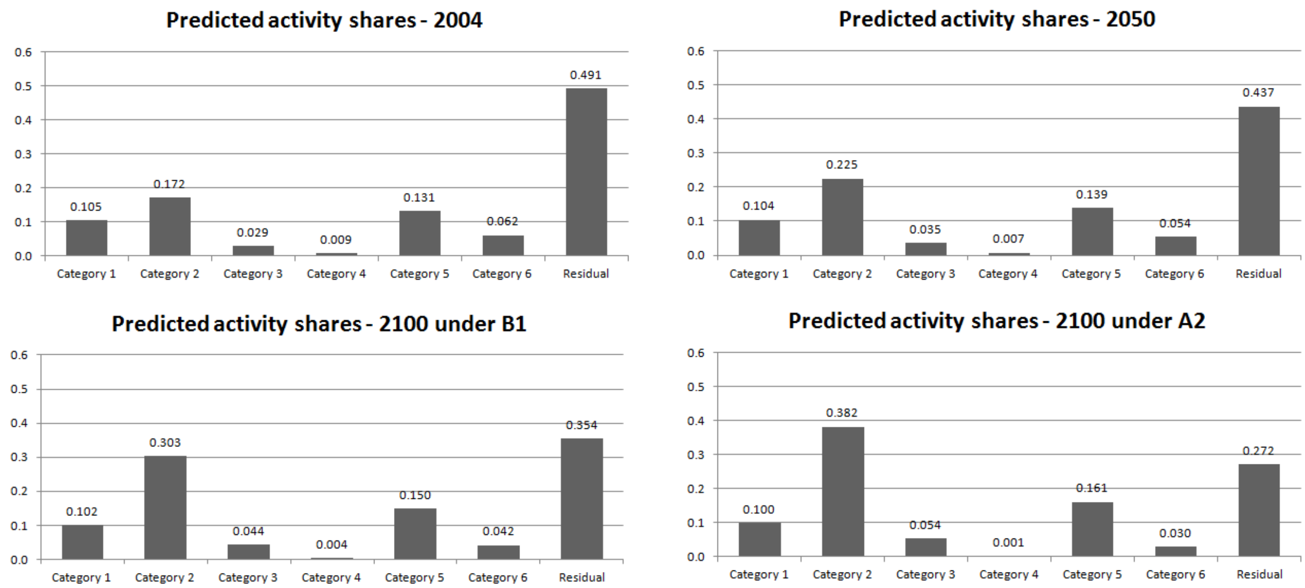
* significant at 10% level ; ** significant at 5% level ; *** significant at 1% level

The results from the imputations that predict recreation choice currently, and as the climate warms are depicted in figure 3.3, and tabulated in table 3.8, and give the predicted activity shares as temperature rises while holding other explanatory variables constant. The bar charts presented depict the expected decrease in time spent at accommodation, relaxing, and pursuing indoor leisure. In the medium-term (by 2050) changes in recreation choices are expected to be smaller compared to the predicted long-term changes under both the A2 and B1 climate scenarios. Both scenarios predict a large increase in time spent at the beach, and a modest increase in time spent at water sports, offset by a decrease in time spent staying at one's accommodation and indoor leisure.

Table 3.8: Predicted share of time spent on each activity category - currently and under global warming scenarios

	Category 1 Land Sports	**Category 2 Beach**	**Category 3 Water Sports**	**Category 4 Field Sports**	**Category 5 Outdoor**	**Category 6 Indoor**
			Current Situation			
Mean	0.105	0.172	0.029	0.009	0.131	0.062
Std. Dev.	0.036	0.139	0.034	0.017	0.126	0.023
			Under B1 Scenario by 2050			
Mean	0.104	0.225	0.035	0.007	0.139	0.054
Std. Dev.	0.036	0.139	0.034	0.017	0.126	0.023
			Under A2 Scenario by 2050			
Mean	0.103	0.251	0.038	0.006	0.143	0.050
Std. Dev.	0.036	0.139	0.034	0.017	0.126	0.023
			Under B1 Scenario by 2100			
Mean	0.102	0.303	0.044	0.004	0.150	0.042
Std. Dev.	0.036	0.139	0.034	0.017	0.126	0.023
			Under A2 Scenario by 2100			
Mean	0.100	0.382	0.054	0.001	0.161	0.030
Std. Dev.	0.036	0.139	0.034	0.017	0.126	0.023

Figure 3.3: Predicted shares of time spent on each activity category



Medium-term (by 2050) predicted shares are shown under the B1 scenario only, since they are very similar to the medium-term A2 predictions. Residual category is calculated as 1-(sum of category 1 to category 6 predicted shares).

3.4.1 Future recreation at Lake Tahoe

Many of the environmental challenges facing the Lake Tahoe area are anthropogenic in nature, and are caused in part by the influx of visitors to the lake [42]. Visitors to Lake Tahoe beaches and water put particular strain on the ecosystem as they can introduce invasive species, algae, and pollute the Lake. Understanding the trends in beach and water visitors' use of the area will enable Lake managers to build and design preemptive strategies and infrastructure to mitigate the environmental harm from increased visitor use, as well as ensure that the Lake's amenities can be enjoyed safely. From the above results summarized in table 3.8, we see that summer visitors' predicted share of time spent at the beach (category 2) will increase from 17% of the day to between 22% and 25% of the day by 2050. Similarly, the predicted share of time spent on water sports (category 3) will increase from 2.9% to 3.5-3.8% by 2050. In order to understand the magnitude and potential policy implications of this behavioral shift, we translate the changes in time use into an estimate of changes in visitor volume in this sub-section.

To do so we first require some estimate of overall visitation trends to Lake Tahoe. These data are derived from annual, or bi-annual, visitor expenditure data compiled in the "2015 North Lake Tahoe Tourism Master Plan" [75][4]. This gives a rough approximation of the trend in visitor volume at Lake Tahoe for 2003-2012. These data are fitted with a linear trend line which is used to predict the number of visitors in the year 2050. There is strong potential for this trend to vary over time due to many factors, including increases in temperature, whereby residents of the surrounding urban areas will seek to cool down in the cold waters of Lake Tahoe, and the surrounding mountainous region, which would lead to an overall upward deviation from the estimated visitation trend. Due to the uncertainties in our estimation of the visitation trend we only predict overall visitation changes in the medium-term (to 2050), and note that, without the implementation of any measures that restrict visitation, the figures presented below are likely to be conservative estimates.

Combining the estimates of the trend in visitation with the temperature driven changes in the share of time spent at Lake Tahoe beaches leads to a predicted 130-160% increase in the number of person/days spent at Lake Tahoe beaches. Completing the same calculation using

[4] Annual visitors is estimated as follows: We first adjust the total expenditure data by the CPI to constant 2012 dollars, then we divide this figure by the estimated average daily expenditure per person in 2012, which is $155, to get an estimate of person/days spent at the Lake. We can then divide by the average visit length of three days to get an estimated number of persons. All figures for this calculation come from the "2015 North Lake Tahoe Tourism Master Plan" [75].

the estimates relating to water sports yields a 115-133% predicted increase in person/days spent on the water. These estimates again do not account for any overcrowding effects or policy changes that may limit beach and water use. In any case, the figures are striking in that summer visitor volume to Lake Tahoe beaches and waters will more than double by 2050 as a result of increased overall visitation, and an increased demand for beach activities on the part of visitors due to warmer temperatures.

3.5 Conclusions

The presented work investigates the relationship between visitor activity choices in the Lake Tahoe area and ambient temperatures, in order to understand how recreation choices will change as temperatures increase due to global warming. Data on visitors' recreation choices come from a visitor time use diary survey performed at many sites around Lake Tahoe throughout the summer of 2004. The data are analyzed using mixed models which account for the multiple potential sources of confounding factors through a nested random/fixed effects approach. Each regression relates the proportion of time spent on a particular category of activities to household level explanatory variables and temperatures.

The regression output shows that temperature drives the allocation of time between recreation options; in particular, the shares of time spent at the beach, on the water, and indoors are influenced by temperature to a statistically significant degree[5]. We investigate the implications of these findings for future recreation choices at Lake Tahoe in order to better prepare management policy and practice for the behavioral changes that global warming will induce. Specifically, the models suggest that as the climate warms visitor time use will shift towards an increase in beach and water activities and a corresponding decrease in indoor activities and time spent at the visitor's accommodation. This information is especially poignant for beach and water managers since beach and water use can cause environmental problems, and is susceptible to overcrowding during the summer months.

Using rough estimates of the trend in overall visitation to the Lake Tahoe area we estimate that by 2050 rising temperatures and an increased number of visitors to the area will have increased beach demand by 130-160% and water use demand by 115-133%. For beach and water managers this means that infrastructure, capacity, and budgets will need to increase in

[5] A the 5% level of α.

order to deal with more than a doubling in visitor volume. Previous research has shown that visitors are willing to abide by regulations for the purpose of protecting natural resources, but are generally opposed to regulations which limit the freedom to visit specific areas [17]. This insight, taken together with the findings herein that the demand for beach and water use at Lake Tahoe will greatly increase, suggests that Tahoe managers should begin to plan and test regulations and infrastructure that will help protect the water, beaches, and recreation values of the Lake.

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Appendix A

A.1 Estimating the UNSD zone effects

We estimate the ATT for a home being in a downstream school district (UNSD 1-3) *vis a vis* an upstream school district (UNSD 3-5), both before and after the intervention year (2012 for most cases). These estimations use the bias-adjusted nearest-neighbor matching estimator shown in (1.2) to derive the ATT between any UNSD zone pair. Matches are based on bedrooms, bathrooms, and square footage, with perfect matching enforced on sale year. Matching balance is optimized using the GenMatch algorithm as described in the main text. The bias-adjustment step accounts for any discrepancy in bedrooms, bathrooms or square footage between a pair of matched homes. Using both a pre and post-intervention ATT for each UNSD zone pair allows us to account for time-variant quality differences between school districts, something traditional spatial fixed effects do not allow for.

The data used to estimate these spatial ATTs are all valid home sales from homes that are **not** within the 500m corridor along Johnson Creek both pre-intervention (1997-2011) and post-intervention (2013-2014). Thus, we avoid any confounding between the spatial ATT estimates and the East Lents project. The estimated spatial ATTs are shown in table A.1. The two $\hat{T}_{i,j}$ terms that are needed exclusively in the Tideman-Johnson estimation, UNSD 1 pre and post *vis a vis* UNSD 2, have their pre and post estimation samples defined relative to 2006, as this was the year of the Tideman-Johnson intervention. These values take the place of the $\hat{T}_{i,j}$ terms in equation (1.16) for all 2SBCME estimations. The total sample counts for each $\hat{T}_{i,j}$ estimation are given in table A.2.

Table A.1: Estimated ATTs of school district effects in $000's

		Downstream	**School**	**District**	**Zones**	
	UNSD 1 Pre	**UNSD 1 Post**	**UNSD 2 Pre**	**UNSD 2 Post**	**UNSD3 Pre**	**UNSD 3 Post**
UNSD 2	27.26	31.72	-	-	-	-
	(2.62)	(7.42)	-	-	-	-
UNSD 3	25.74	23.35	80.79	133.54	-	-
	(1.34)	(3.18)	(3.43)	(4.29)	-	-
UNSD 4	19.24	27.18	72.70	170.01	-4.82	1.86
	(2.07)	(3.08)	(4.01)	(5.72)	(1.50)	(3.04)
UNSD 5	9.30	14.14	80.37	156.52	-22.97	-16.86
	(1.48)	(2.68)	(3.76)	(4.51)	(1.62)	(2.95)

Std. Errors given in parentheses

Table A.2: Sample sizes used in estimating first stage ATTs

		Downstream	**School**	**District**	**Zones**	
	UNSD 1 Pre	**UNSD 1 Post**	**UNSD 2 Pre**	**UNSD 2 Post**	**UNSD3 Pre**	**UNSD 3 Post**
UNSD 2	18587*	6666*	-	-	-	-
UNSD 3	18161	2986	16242	13051	-	-
UNSD 4	8205	2795	15899	12860	9820	1781
UNSD 5	18192	3412	16280	13477	11655	2398

*The pre and post periods for UNSD 1 to UNSD 2 ATT estimations are defined relative to 2006 as these figures are used only in the Tideman-Johnson estimation. All other pre and post periods are defined relative to 2012 since these figures are used in the East Lents estimation.

A.2 Annex of tables

Table A.3: Characteristics of home sales used in Tideman-Johnson estimation pre and post-intervention

		Pre -	**Intervention**	**Sample**	**(1990-2005)**	
		mean	**std. dev.**	**median**	**min**	**max**
Upstream	price($1000's)	208.64	101.17	184.98	88.49	898.21
n=649	bedrooms	2.79	1.02	3	0	8
	baths	1.79	0.83	2	0	6
	square footage	1400.70	526.89	1320	576	5045
Downstream	price($1000's)	285.62	140.87	236.21	117.39	898.21
n=269	bedrooms	2.91	0.96	3	0	7
	baths	1.99	0.91	2	1	6
	square footage	1583.44	660.97	1505	650	5045
		Post-	**Intervention**	**Sample**	**(2007-2014)**	
		mean	**std. dev.**	**median**	**min**	**max**
Upstream	price($1000's)	211.21	64.90	208.43	88.32	511.06
n=200	bedrooms	2.64	1.10	3	0	6
	baths	1.66	0.80	1	1	6
	square footage	1298.95	488.68	1161.00	325.00	3252.00
Downstream	price($1000's)	399.24	165.52	362.54	148.18	884.52
n=105	bedrooms	2.81	1.07	3	0	5
	baths	1.98	0.90	2	1	6
	square footage	1512.35	553.75	1482	738	3328

The reader may notice that there are a few homes in our sample with zero values for bedrooms and/or bathrooms. This is due to the strict definitions for bedrooms and bathrooms used by the county assessor offices, such that a room that would colloquially be referred to as a bedroom or bathroom is not always counted as such in our data.

Table A.4: Home sales price ($1000's) statistics from Tideman-Johnson sample by unified school district (UNSD)

UNSD	Pre - Obs.	Intervention mean	Sample std. dev.	(1990-2005) min	max
1	512	176.25	47.00	88.49	444.94
2	406	249.49	131.87	89.38	898.21
	Post-	**Intervention**	**Sample**	**(2007-2014)**	
1	149	215.67	66.19	88.32	444.89
2	156	333.51	168.77	102.20	884.52

Appendix B

B.1 Gibbs Sampler Details

The model given in (2.3) and (2.4) can be concisely written as:

$$y_{is} = \begin{cases} 1, & \text{if} \quad v_{is} > 0, \\ 0, & \text{otherwise,} \end{cases}$$

with

$$v_{is} = \frac{v_{is}^*}{\gamma_i} = d_s \mathbf{D}_s' \beta_{is} - P_{is} + d_s \epsilon_{is}, \quad \epsilon_{is} \sim N(0, \sigma_i^2),$$

with $\sigma_i^2 \sim IG(r, \varrho)$, and where

$$\beta_{is} = (1 + \mathbf{z}_{is} \boldsymbol{\alpha}')\, \beta_i,$$

and $\beta_i = \bar{\beta} + \delta_i, \quad \delta_i \sim N(0, \nu^2),$

where y_{is} is respondent i's choice in scenario s, and $IG(r, \varrho)$ refers to the inverse-gamma density with shape r and scale ϱ. Thus the relevant parameters of the prior distributions are ϱ, $\bar{\beta}$, and ν^2. We select a Gamma distribution as prior of ϱ with shape a_ϱ and scale A_ϱ, and the natural conjugate prior for $\boldsymbol{\alpha}$ is $N(a_{\boldsymbol{\alpha}}, A_{\boldsymbol{\alpha}})$, where $a_{\boldsymbol{\alpha}}$ and $A_{\boldsymbol{\alpha}}$ are the mean vector and the covariance matrix of a multivariate normal distribution. The natural conjugate priors for the primary parameters $\bar{\beta}$ and ν^2 are chosen as

$$\begin{aligned} \nu^2 &\sim IG(a_\nu, A_\nu), \\ \bar{\beta}|\nu^2 &\sim N\left(a_{\bar{\beta}}, \frac{\nu^2}{A_{\bar{\beta}}}\right), \end{aligned} \tag{3.2}$$

Table A.5: Characteristics of home sales used in East Lents estimation pre and post-intervention

		Pre -	**Intervention**	**Sample**	**(1997-2011)**	
		mean	**std. dev.**	**median**	**min**	**max**
Upstream	price($1000's)	252.50	86.80	232.04	96.60	779.63
n=1019	bedrooms	3.11	1.14	3	0	10
	baths	2.36	0.80	2	0	9
	square footage	1510.52	530.09	1358.00	624.00	4298.00
Downstream	price($1000's)	203.43	62.64	193.67	89.12	588.00
n=592	bedrooms	2.68	1.15	3	0	11
	baths	1.70	0.84	2	0	9
	square footage	1327.74	492.65	1246.5	325	4579
		Post-	**Intervention**	**Sample**	**(2013-2014)**	
		mean	**std. dev.**	**median**	**min**	**max**
Upstream	price($1000's)	241.27	72.29	231.31	91.67	581.54
n=102	bedrooms	3.10	1.29	3	0	8
	baths	2.34	0.79	2	1	4
	square footage	1662.48	583.26	1466.00	800.00	3762.00
Downstream	price($1000's)	195.63	63.11	188.42	88.32	444.89
n=49	bedrooms	2.61	1.17	3	0	5
	baths	1.57	0.71	1	1	3
	square footage	1309.45	411.08	1282	717	2352

where a_ν refers to the degrees of freedom and A_ν to the scale parameter of the inverted gamma distribution (IG). $\mathbf{a}_{\bar{\beta}}$ and $\mathbf{A}_{\bar{\beta}}$ are the mean and the variance of a multivariate normal (N) distribution, respectively. The numerical settings for all prior parameters are displayed in Table B.1.

The Gibbs sampler proceeds as follows:

1. Draw surplus v_{is} from $p\left(v_{is}|\beta_{is}, \sigma_i^2, y_{is}\right) \quad \forall\, i = 1, \ldots, N$, and $\forall\, s = 1, \ldots, S$,

2. Draw latent coefficients β_i from $p\left(\beta_i|\mathbf{v}_i, \sigma_i^2, \boldsymbol{\alpha}, \bar{\beta}, \nu^2\right) \quad \forall\, i = 1, \ldots, N$,

3. Draw surplus variances σ_i^2 from $p\left(\sigma_i^2|\mathbf{v}_i, \boldsymbol{\alpha}, \beta_i, \varrho\right) \quad \forall\, i = 1, \ldots, N$,

4. Draw coefficients $\boldsymbol{\alpha}$ from $p\left(\boldsymbol{\alpha}|\mathbf{v}_1, \ldots, \mathbf{v}_N, \beta_1, \ldots, \beta_N, \sigma_1^2, \ldots, \sigma_N^2\right)$,

5. Draw the shape parameter of the surplus variances ϱ from $p\left(\varrho|\sigma_1^2, \ldots, \sigma_N^2\right)$,

Table A.6: Home sales price ($1000's) statistics from East Lents sample by unified school district (UNSD)

UNSD	**Pre - Obs**	**Intervention mean**	**Sample std. dev.**	**(1997-2011) min**	**max**
1	416	201.37	53.53	89.12	370.32
2	170	209.52	80.79	90.56	588.00
3	290	250.47	93.07	88.20	779.63
4	41	270.27	64.77	182.22	464.23
5	695	251.34	85.41	96.60	724.00
	Post-	**Intervention**	**Sample**	**(2013-2014)**	
1	39	198.45	66.46	88.32	444.89
2	9	183.66	52.17	129.68	309.23
3	34	239.62	61.67	149.63	448.88
4	6	276.54	30.51	247.38	324.19
5	63	238.04	79.49	91.67	581.54

Table B.1: Prior settings for the Gibbs sampler, where K refers to the number of variables in $\mathbf{z}_{is}$.

Prior name	Prior value
r	$1/2$
a_{ϱ}	1
A_{ϱ}	$1/100$
$\mathbf{a}_{\boldsymbol{\alpha}}$	0
$\mathbf{A}_{\boldsymbol{\alpha}}$	$10 \times \mathbf{I}_K$
$a_{\bar{\beta}}$	0
$A_{\bar{\beta}}$	0.01
a_{ν^2}	$(1+3)/2$
A_{ν^2}	$(a_{\nu^2} \times 0.1)/2$

6. Draw the variance for the latent coefficients ν^2 from $p\left(\nu^2|\beta_1,\ldots,\beta_N,\bar{\beta}\right)$.

7. Draw the primary coefficient $\bar{\beta}$ from $p\left(\bar{\beta}|\beta_1,\ldots,\beta_N,\nu^2\right)$,

The draws from step (1) are aggregated over s to form the vector of surplus draws for each respondent $\mathbf{v}_i$. Sampling from distributions (1), (3), (4), (5), (6), and (7) is standard in Bayesian econometric literature (see e.g. Albert and Chib [4] and Rossi et al. [66]). Sampling from distribution (2) is explained in detail in [62]. We draw 100,000 draws from the Gibbs sampler and keep every 5th draw, which results in 20,000 draws of each parameter. The first 10,000 draws are burn-in and are discarded, which leaves 10,000 draws for inference.