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The Allocation of Time and Risk of Lyme: A Case of Ecosystem Service Income and Substitution Effects

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Abstract Forests are often touted for their ecosystem services, including outdoor recreation. Historically forests were a source of danger and were avoided. Forests continue to be reservoirs for infectious diseases and their vectors—a disservice. We examine how this disservice undermines the *potential* recreational services by measuring the human response to environmental risk using exogenous variation in the risk of contracting Lyme Disease. We find evidence that individuals substitute away from spending time outdoors when there is greater risk of Lyme Disease infection. On average individuals spent 1.54 fewer minutes per day outdoors at the average, 72 U.S. Centers for Disease Control and Prevention, confirmed cases of Lyme Disease. We estimate lost outdoor recreation of 9.41 h per year per person in an average county in the Northeastern United States and an aggregate welfare loss on the order $2.8 billion to $5.0 billion per year.

Keywords Adaptation · Resource allocation · Risk · Economic-Epidemiology · American Time Use Survey (ATUS) · Travel cost

1 Introduction

For all but the last instant of human existence forests were scary places, full of fangs and claws, providing net disservices. More recently, humans have learned that forests provide many services, and have reduced the fangs and claws, especially in North America. In North America, and elsewhere, a major benefit of forests is the provision of recre-

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ational opportunities (De Groot et al. 2002, 2012). Yet, the dangers of forests have not been completely eliminated. Perhaps the largest disservice that forests provide is a safe haven for infectious disease and the vectors that carry them. Globally, many novel emerging infectious diseases are associated with forests and wilderness areas (Patz et al. 2005). However, in the heavily populated northeastern United States the pathogen most likely to lurk in a forest as well as in local wooded and grassy areas is *Borrelia burgorferi*, the infectious agent causing Lyme Disease, which is transmitted by the black legged tick.

The existence of pathogens in forests and outdoor spaces reduces the recreational value of forests and outdoor spaces relative to a tick and Lyme Disease-free system. The loss of non-market income [i.e., income not flowing through the cash draw (Fisher 1906)] represents an income effect, but this income effect can be, and often is, partially offset by a substitution effect. An income effect exists irrespective of any treatment costs, and exists because people are "endowed" with a lower quality asset that provides lower valued service flows. The income effect is the forgone utility flow that results from substituting to lower quality services in response to the higher expected cost of utilizing services as a result of disease risk. All individuals who would consume outdoor leisure absent Lyme Disease risk suffer a welfare loss because of this effect. The direct expenditures on treatment of infection and expenditure on preventive measures such as insect and tick repellent or forgone recreational expenditures – the two measures most used to measure the cost of disease (Zinsstag et al. 2007; Perrings et al. 2014) are at least partially transfer payments, and are unlikely to reflect the true economic costs.[1] Individuals can substitute lower valued activities to partially offset these losses. Recent studies in economic epidemiology have hypothesized (Fenichel et al. 2011) and uncovered (Fenichel et al. 2013; Bayham et al. 2015; Springborn et al. 2015) behavioral responses – substitution effects – to disease risk. In the case of Lyme Disease, people may allocate time away from outdoor activities in order to avoid infection. Indeed, survey studies have found that residents in the Northeast view avoiding tick habitat as a primary preventative activity (Herrington et al. 1997; Phillips et al. 2001; Herrington 2004).

We focus on Lyme Disease in the Northeastern United States to test the behavioral substitution hypothesis and estimate welfare loss. Lyme Disease is prevalent across the northeastern United States and around the Great Lakes. It causes fever, headaches, fatigue and a skin rash, and requires several weeks of antibiotics to treat, causing utility loss to infected individuals. It can also be prevented by the use of repellents and removing ticks, as well as costly efforts to remove tick habitat.[2] Lyme Disease is therefore costly if contracted and costly to prevent. Individuals can be expected to substitute away from activities associated with Lyme Disease risk. If there is a substitution effect, there is likely an income effect, as the risk of Lyme will make individuals worse off compared to a world without Lyme Disease. This income effect is the welfare loss due to the risk of Lyme Disease. We test the hypothesis that people substitute away from outdoor leisure activity in response to Lyme Disease risk, using county level case reports from the CDC and outdoor and indoor activity reported in the American Time Use Survey (US Department of Labor. Bureau of Labor Statistics 2015).[3] Evidence of

[1] Given large imperfections in medical service and health insurance markets, the degree to which treatment costs reflect true economic cost or transfer payments is an important research question beyond the scope of this paper. Some of these expenditures are certainly real costs. By excluding them from our analysis we provide a lower bound on the total welfare loss associate with Lyme Disease.

[2] http://www.cdc.gov/lyme/, or the ridiculously costly approach of vaccinating short-lived intermediate hosts like mice (Tsao et al. 2004).

[3] http://www.cdc.gov/lyme/stats/index.html.

a substitution effect in addition to an income effect leads to the question, “how much would people be willing to pay for a Lyme Disease free world?”

We contribute to the literature on ecosystem services and economic epidemiology. First, we show how standard microeconomic theory related to income and substitution effects maps to non-cash income derived from ecosystem services. To do this we consider utility maximization subject to a budget constraint that includes leisure time and risk of infection, similar to the literature on the valuation of ecosystem quality (Gallagher and Smith 1985; Smith 1987; Foster and Just 1989; Phaneuf and Requate 2017). This analysis highlights that accounting for income and substitution effects associated with changes in the quality of ecosystem services is important, and ignoring these behavioral effects can easily lead to underestimation when only cash income is considered. Second, we use spatial variation in Lyme Disease risk across the northeastern United States to test the hypothesis that individuals substitute away from “consuming” ecosystem services when the quality of those services is diminished or the cost or risks of consuming the ecosystem service is increased. In so doing, we contribute to the emerging literature on behavioral responses to infectious disease risk and feedbacks to infection processes. In the case of Lyme Disease we show that understanding these feedbacks is important for measuring the prevalence of infectious agents and welfare loss. Specifically, we apply a GMM estimation strategy (Arellano and Bond 1991; Roodman 2009), and show the relationship between reported Lyme Disease cases and time outdoors is endogenous (one typically must be outdoors to contract Lyme). Therefore, case counts are not a valid index of disease prevalence in the environment. After controlling for the endogeneity of Lyme Disease risk, we find that in locations where cases are more prevalent, people spend less time outdoors relative to the counterfactual case of lower or no disease prevalence.

2 Theoretical Model

The canonical microeconomic consumer problem involves an agent choosing between two goods subject to an additive monetary budget constraint (Varian 1992). Foster and Just (1989) use a model with uncertainty to show an increase in the risk and uncertainty related to a bad causes an individual to reduce his exposure. We follow the canonical models that include a quality attribute (Freeman et al. 2014; Phaneuf and Requate 2017) and Foster and Just (1989) to consider the choice of whether to engage in outdoor activities or spend time indoors, with one small difference. We are interested in the case where the increased risk of contracting Lyme Disease (where risk consists of the probability and the cost of suffering from Lyme Disease) increases the expected cost of the outdoor experience. Lyme Disease risk is the quality attribute that individuals cannot directly effect. However the quality attribute is not ambient, individuals are only exposed to Lyme Disease through allocating time to outdoor activity. Therefore, we restrict the general model (Freeman et al. 2014; Phaneuf and Requate 2017) so that the shadow price of Lyme Disease risk is a component of the price of outdoor time. Individuals choose to distribute their leisure time between outdoor activities, y, and indoor activities, z. The risk (the damages and probability) of coming into contact with infected ticks and being exposed to Lyme Disease is represented by the index L, and depends on the prevalence of infected ticks in an area. Individuals maximize utility $U(y, z, m)$ subject to a budget constraint $m = p_y(L)y + p_z z$, where m is full income (Phaneuf and Requate 2017) and $p_y(L)$ and p_z are the expected costs of each activity, which include the opportunity cost of time, regardless of whether Lyme Disease is actually contracted.[4,5] The expected cost of outdoor activity increases with risk of infection, $\frac{\partial p_y}{\partial L} > 0$, because individuals must account for the cost of potential infection in addition to the opportunity cost of time. We assume that tick encounters are random so the component of outdoor leisure cost associate with Lyme Disease is constant, conditional on the riskiness of the area, per unit time exposed to a given area.[6] Substituting the constraint into the utility function provides the representative agent's problem

$$\max_y \bar{U} = U\left(y, m - \frac{p_y(L)}{p_z} y\right). \tag{1}$$

The first order optimality conditions imply the relation,

$$\frac{d\bar{U}}{dy} = \frac{\frac{\partial U}{\partial y}}{p_y(L)} - \frac{\frac{\partial U}{\partial z}}{p_z} = 0 \tag{2}$$

where the marginal utility per dollar of outdoor activity, $\frac{\frac{\partial U}{\partial y}}{p_y(L)}$ must be equal to the marginal utility per dollar of indoor activity $\frac{\frac{\partial U}{\partial z}}{p_z}$. The marginal utility per dollar of outdoor activity is conditional on individual's risk of contracting Lyme Disease risk in a given area, L.

Behavioral changes due to Lyme risk impact welfare. Changes in welfare depend on implicit property rights and ability of individuals to substitute between activities (Freeman et al. 2014). We directly observe a world with Lyme Disease (point A in Fig. 1) and are interested in the effect of a reduction in Lyme Disease risk. If Lyme Disease risk is removed then the price of outdoor activity $p_y(L)$ falls to $p_y(0)$ (Fig. 1). Individuals increase their time spent outside, shifting from point A to point B. Individuals can also attain utility, U', through an increase in income represented by the dashed budget line that is tangent to the utility indifference curve at point C. The move from C to B represents the substitution effect, and the move from A to C is the income effect. We relate this figure to our empirical specification in greater detail in Sect. 3.1.

The Slutsky equation (Eq. 3) (Varian 1992) formalizes the changes shown in Fig. 1.

$$\frac{dy\left(p_y^*, p_z^*, m^*\right)}{dp_y(L)} \frac{dp_y(L)}{dL} = \left(\frac{\partial y^*\left(p_y^*, p_z^*, \bar{U}\right)}{\partial p_y(L)} - \frac{\partial y\left(p_y^*, p_z^*, m^*\right)}{\partial m} y^*\right) \frac{dp_y(L)}{dL} \tag{3}$$

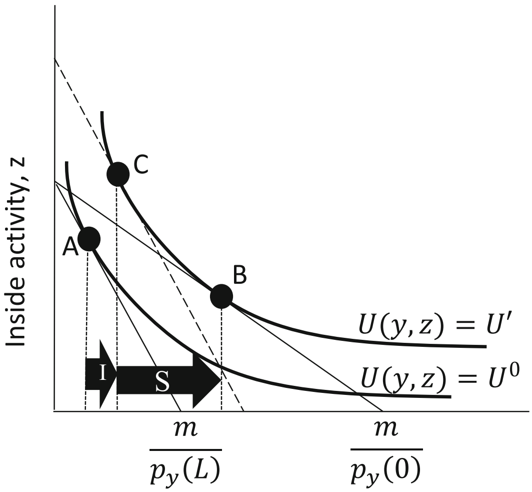
Increases in Lyme prevalence induces an effective income reduction, $\frac{\partial y}{\partial m} y^* \frac{\partial p_y(L)}{\partial L}$, where there is a change in the amount of time spent outdoors due to a change in income, $\frac{\partial y}{\partial m}$, multiplied by the change in outdoor activity consumed, y^*, multiplied by the change in the

[4] We assume that Lyme Disease related decisions do not influence income from labor, which implies time is not reallocated to labor. We find no evidence of time reallocation to labor in the empirical section of the paper.

[5] The canonical model (Freeman et al. 2014; Phaneuf and Requate 2017) express U slightly more generally as $U(y, z, m, L)$. In the canonical model individuals experience an ambient level of the quality attribute, in this case L. In our setting, individuals only experience a level of L if they consume y, which is a non-essential good. This restriction allows us to derive an outdoor time demand function that nests inside the general demand function for y presented in the canonical model. Importantly, everyone who alters behavior to avoid infection suffers a welfare loss from Lyme Disease, not just the people who contract infection.

[6] Increased use of an area by people does not increase the prevalence of infected ticks. Humans do not shed enough pathogen to infect new ticks, so there is no feedback from people to quantity of infected ticks.

Fig. 1 Income and substitution effects associated with the optimization of activity choice subject to a time budget



price of outdoor activity that results from a change in the prevalence of Lyme Disease, $\frac{\partial p_y(L)}{\partial L}$.[7] A greater expected price of outdoor activity causes individuals to be worse off because they cannot afford their Lyme-free bundle of activities. Increases in Lyme prevalence also lead to a substitution effect, where the change in the relative price of outdoor activity compared to indoor activity causes individuals to substitute towards indoor activities that would otherwise be less preferable.

3 Empirical Model

We hypothesize that individuals respond to an increase in the risk of contracting Lyme Disease by reducing the time they choose to spend on outdoor recreation.[8] Fragmented areas of forest have a higher density of infected ticks. In the Northeast, suburban areas including recreational parks, baseball diamonds, and soccer fields are fragmented forests with a nontrivial threat of Lyme Disease (Allan et al. 2003). We regress time spent on outdoor activity away from one's home on Lyme Disease cases in the area. We include characteristics of the region to control for other factors that may influence outdoor recreation. However, the act of recreating outdoors exposes people to risk that directly influences the likelihood of a Lyme Disease case occurring in a region. Thus, Lyme Disease cases and time spent outdoors are jointly determined, and Lyme Disease prevalence is endogenous.

3.1 Estimation and Identification Strategy

We test the hypothesis that an increase in the risk of Lyme Disease reduced the amount of time people spend on outdoor recreation. Our goal is to identify the causal effect of Lyme Disease risk, measured by prevalence in the area, on outdoor recreation decisions.

[7] The direct effect of a change in Lyme Disease risk is multiplicatively separable in the Slutsky equation due to our restrict that the quality effect of Lyme Disease risk to enter through the full price of consuming outdoor recreation.

[8] A list of all activities included in the analysis is provided in Table 3 in the appendix. All activities are also limited using the ATUS variable TEWHERE to include only those taking place outdoors and away from home.

However, regressing outdoor recreation time on the prevalence of Lyme Disease within an area is not valid because Lyme prevalence is clearly not exogenous as people acquire infection when they spend time outdoors. Consequently, OLS estimators are likely biased and inconsistent.

We employ a dynamic panel estimation strategy following Arellano and Bond (1991) and Blundell and Bond (1998) designed to address the endogeneity of Lyme Disease prevalence and outdoor recreation time. The GMM estimator jointly estimates a system of two equations: one in levels, and one in differences.

$$y_{it} = \alpha y_{i,t-1} + \delta_1 L_{it} + \delta_2 L_{it}^2 + \boldsymbol{x}_{it}\boldsymbol{\beta} + \boldsymbol{c}_i\boldsymbol{\gamma} + \psi_{it} \text{ where } \psi_{it} = u_i + \varepsilon_{it} \tag{4a}$$

$$y_{it}^* = \alpha y_{i,t-1}^* + \delta_1 L_{it}^* + \delta_2 L_{it}^{*^2} + \boldsymbol{x}_{it}^*\boldsymbol{\beta} + \varepsilon_{it}^*, \tag{4b}$$

where y_{it} is the average daily time in minutes spent on outdoor activities from May to November in year t by individuals who live in geography i (county or Census Statistical Area), L_{it} is the number of cases of Lyme Disease reported in geography i in year t where we include a squared term to allow for a nonlinear response to disease risk, $\boldsymbol{x}_{it}$ is a vector of time-varying controls that include annual averages of maximum and minimum daily humidity and temperature in each area as well as precipitation, $\boldsymbol{c}_i$ is a vector of time-invariant controls that include the percentage of each area that is classified as wilderness, municipal park, national park and the local expenditure on parks and recreation, and ψ_{it} is an idiosyncratic error where u_i is fixed over time and ε_{it} varies over time and geography. The asterisk denotes the forward orthogonal transformation alternative to the first-difference transformation (Arellano and Bover 1995).[9] The moment conditions are constructed based on Eqs. 4a and 4b, and the parameters are estimated jointly.

Several empirical issues complicate our ability to establish a causal relationship between Lyme Disease cases and changes in outdoor recreation. The spatial variation in permanent physical characteristics of geographic areas may influence the attractiveness of outdoor activity. For example, some areas have greater access to wilderness, national parks, or municipal parks. Urban areas may have little access to outdoor activities, so that most recreation is performed indoors. We account for this variable access with time-invariant controls, $\boldsymbol{c}_i$, that capture the availability of outdoor amenities. Weather also likely influences the attractiveness of outdoor activities. We control for temperature, precipitation and humidity, which at high levels may discourage certain forms of outdoor activity. We focus on the Northeast United States in the warm weather months, which are characteristically humid and may make outdoor recreation less desirable.

Individuals may choose where to live based on their tastes and desires for access to outdoor amenities (i.e., sorting). Median income and education levels vary by geography, and these are most certainly related to the desire and ability to spend time on outdoor recreation. We include geography-specific fixed effects in several specifications to control for these confounding factors. We also include lagged values of outdoor recreation time to control for habit formation. For many people hiking, running or playing sports is a hobby that may have

[9] The forward orthogonal transformation of x is defined as

$$x_{i,t}^* \equiv \sqrt{\frac{T_{it}}{T_{it}+1}}\left(x_{it} - \frac{1}{T_{it}}\sum_{h>t} x_{ih}\right),$$

where the sum is taken over all future available observations, T_{it} (Roodman 2009). This transformation preserves observations when there are gaps within panels that would otherwise be removed under a first-difference transformation.

required significant investments in physical training or equipment. Their past habits may inform their current levels of activity.

Our identification strategy relies on using Lyme Disease prevalence from past years as instruments for endogenous covariates, contemporaneous Lyme Disease prevalence and the past year's outdoor recreation time (lagged dependent variable). The validity of our instruments depends on whether Lyme Disease prevalence in the past is correlated with current decisions to recreate outdoors only via current Lyme Disease prevalence. Specifically, lagged observations of Lyme Disease cases, $L_{i,t-s}$ where $s \geq 2$ lags, instrument current observations in the transformed Eq. 4b, and lagged transformed[10] case observations, $\Delta L_{i,t-s}$ where $s \geq 2$ lags, to instrument current observations in the levels Eq. 4a. The model is exploiting the information from the observations and deviations from trends in the time series within each geography. In addition, all exogenous covariates, $\boldsymbol{x}_{it}$ and $\boldsymbol{c}_i$, are used as instruments when included in the specification.

The logic behind our choice of instruments follows from infectious disease dynamics. The positive trend of cases during the early stages of an outbreak signals an increase in future cases. Moreover, decisions to spend more time outdoors today have no direct impact on Lyme Disease prevalence in the past in contrast to the jointly determined contemporaneous Lyme Disease prevalence. However, lagged Lyme Disease cases might still be endogenous if lagged outdoor recreation time is omitted from the model but actually drive lagged cases (omitted variables bias). The Arellano–Bond test for autocorrelation provides evidence that outdoor recreation trends (first differences) of lags two and further are not significantly correlated with contemporaneous outdoor recreation trends. This suggests that lags two and deeper of confirmed cases are exogenous and valid instruments for contemporaneous cases.

All regressions are conducted in Stata 12 (StataCorp 2011) using the *xtabond2* package (Roodman 2009). We use the two step estimator that is robust to within-panel autocorrelation and heteroskedasticity. Standard errors are estimated based on the two-step correction (Windmeijer 2005).

3.2 Data

The data for this study come from several sources spanning the Northeastern US and Northern Midwest, and the final dataset spans from 2003 to 2012. The CDC's website provides Lyme Disease case count by year and county code for the years 2000–2014 (CDC 2015).[11] Values are the number of reported cases, which from 2000 to 2007 reflect a previous case definition that changed in 2008. The 2008 case definition allows the reporting of confirmed and probable cases. The case definition from 2000 to 2007 required either discovery of the initial skin lesion, or a late manifestation of Lyme Disease that consisted of joint swelling, arthritis, or symptoms in the nervous or cardiovascular systems as well as lab confirmation. This definition was updated in 2008 so that confirmed cases required either the initial lesion with known exposure to Lyme Disease, or the lesion with no known exposure but lab confirmation, or late manifestation with lab confirmation. We used confirmed case counts under the relevant case definition at the time. Cases by geographic location are plotted in Fig. 2. The bulk of cases are located on the east coast of the United States, between Massachusetts and Washington

[10] When transformed lagged observations are used as instruments in the levels Eq. 4a, the conventional first-difference transformation, $x_{i,t} - x_{i,t-1}$, is applied. The forward orthogonal deviations transform would be inappropriate for lags because it would include the contemporaneous observations as part of the average future observations, which is hypothesized to be endogenous motivating the instrumental variables approach to begin with.

[11] http://www.cdc.gov/lyme/stats/index.html.

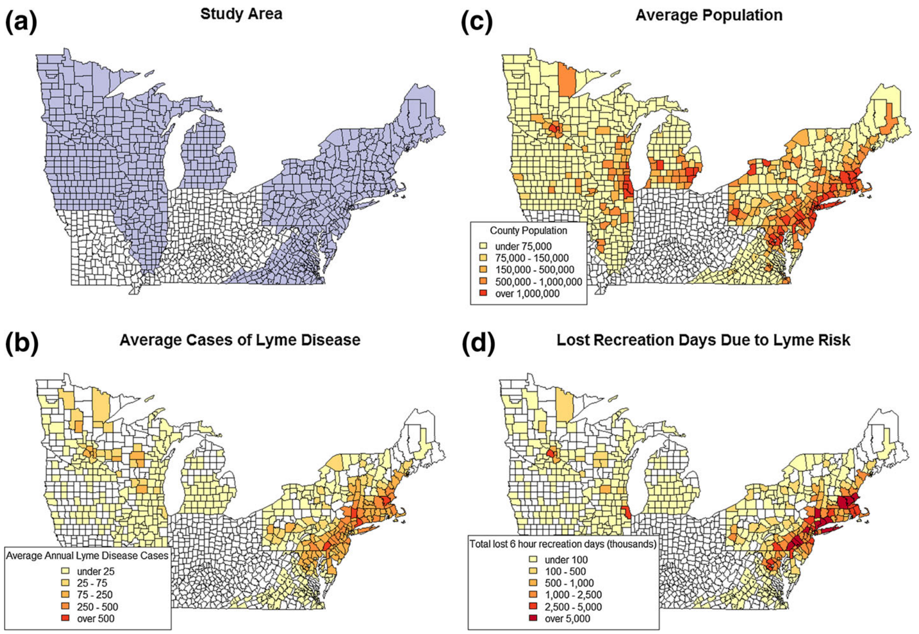


Fig. 2 Maps showing **a** our study area, including all shaded counties, **b** average Lyme Disease cases, **c** average population, and **d** estimated minutes of lost outdoor time per year as a result of Lyme Disease risk. White counties are not represented in the final dataset

D.C. There are additional loci of confirmed Lyme Disease cases in the Midwest, focused on populated areas.

The American Time-Use Survey provides individual time-use data between 2003 and 2013 (US Department of Labor. Bureau of Labor Statistics 2015). The survey is administered at the county (FIPS), Core Based Statistical Area (CBSA), or New England City and Town Area (NECTA) level depending on population to ensure anonymity. We refer to all of these as geographies. Survey respondents report a 24-h diary of activities and locations for every minute of the day. The survey is conducted by phone, transcribed, and two individuals independently encode the activity and location from nearly 400 activity codes and 25 location codes.

We construct a measure of outdoor activity by year and by geography to conform to the panel structure of the CDC Lyme Disease data. We compile a list of outdoor activities including hiking or walking outdoors as well as organized sports, such as football, that often involve spending time in grassy fields lined by higher grasses or trees.[12] We calculate the mean time spent on the set of outdoor activities in each year during the months May-October, the time when ticks are most active, within each geography. Survey weights are used to ensure that average durations are representative of the population in each year and geography. Activities are tied to the individual's geography of residence, so that it is assumed all activities take place in the respondent's county of residence. We also exploit information in the ATUS on where an activity took place. We distinguish between outdoor activity away from home and activities in the home and yard. We are careful to measure and exclude travel time in one's vehicle, which we use in our travel cost analysis.

[12] The complete list is in the Appendix in Table 3.

In order to account for the relative accessibility, quality of outdoor recreation opportunities, and tick habitat, we include several measures of the quality of outdoor recreation. These include measures of the percentage of each area that is classified as wilderness, a municipal park, a national park and the local expenditure on parks and recreation (Bieri et al. 2013). These variables do not vary over time and measure the availability of high quality recreation areas.

Weather likely influences individuals' decisions to engage in outdoor recreation. We collect daily precipitation, and maximum and minimum humidity and temperature in each geography. We access the daily records from the National Weather Service weather station located closest to the center of each area of geography (centroid of GIS polygon) using the R package weatherData (Narasimhan 2015). In order to merge the weather data with the Lyme Disease and activity data, we calculate the mean monthly precipitation during the tick season, as well as the mean daily maximum temperature, minimum temperature, maximum humidity, and minimum humidity over the months May–October in each year.

The amount of suitable tick habitat may affect the size and activity level of local tick populations and thus the risk of acquiring Lyme during recreation activities. We use spatial analysis at the county level to calculate the density of small patches (patches/sq km) of deciduous forest less than 2 ha (Allan et al. 2003). We calculate the number of patches and the percent area in patches in 2001, 2006, and 2011 from the National Land Cover Database (Fry et al. 2011). We then linearly interpolate the predicted tick habitat area for all years to be used as an additional instrument for confirmed Lyme Disease cases. In addition, we gather county level population data from the US Census for population counts, or estimates of counts for years between each Census, by county code (Census 2015). Population is plotted in Fig. 2, and roughly matches the spread of Lyme Disease cases.

Our study area includes the Northeastern United States (from Virginia north) and the Midwest. The extent of our study area is included in the maps in Fig. 2, however we do not have data for each individual county in these states. In order to match the various spatial extents of the data, it was necessary to aggregate observations recorded at high spatial resolution (e.g., counties) up to the largest spatial extents. These units of measure range from New England city and town area (NECTA) codes, Core-based statistical area (CBSA) codes and Federal Information Processing Standard (FIPS) codes. ATUS activity data are primarily measured at the NECTA or CBSA level, although they are measured at the FIPS level when areas are not contained within a larger unit. Case counts and population counts were summed to the CBSA and NECTA code level. Similarly, the percentage of each area that is considered wilderness, municipal parks, national parks or parks and recreation budgets were aggregated by taking the mean of smaller geographic areas up to the CBSA or NECTA levels. Activity data are not available for every geography in each month due to the ATUS survey design. Therefore, the final dataset is an unbalanced panel of 845 observations within 172 locations over 9 years. In our specification described in the previous section, locations with few observations are dropped resulting in a dataset of 670 observations in 93 locations, with an average of 7.2 observations per location. Summary statistics for the final dataset are included in Table 1.

3.3 Welfare

Equations 4a and 4b are similar to a Marshallian Demand function, $y\left(p_y(L), p_z, m\right)$ where the price of activities is captured in the vectors x_{it} and c_i that control for the specific characteristics of each area. The impact of Lyme Disease on price and the impact of price on the quantity of outdoor activity are contained in the term $\delta_1\hat{L} + \delta_2\hat{L}^2$. The correct welfare measure must account for the shift from leisure into substitute activities and is not simply

Table 1 Summary statistics for variables

	Mean	Standard deviation	Minimum	Maximum
Confirmed Lyme cases	72.17	127.4	0	1283
Outdoor recreation (minutes)	6.01	16.6	0	210
Population	9.93×10^5	2.35×10^6	9.7×10^4	1.99×10^7
Patches of habitat	4.6×10^4	4.5×10^5	0	4.3×10^6
Max humidity (%)	90.67	5.27	40.00	99.57
Min humidity (%)	48.99	5.25	22.68	73.51
Precipitation (inches)	0.14	0.33	0	7.85
Max temperature (F)	75.36	3.75	59.20	86.25
Min temperature (F)	56.01	3.9	40.88	69.01
River area (meters per square meter)	0.233	0.111	0.076	1.34
Land area (square meters)	4.47×10^9	4.41×10^9	3.89×10^7	2.18×10^{10}
% Wilderness	0.085	0.476	0	8.27
% City parks	0.867	1.51	0	15.68
% Nat parks	0.341	1.203	0	18.541
Parks rec ($ per capita)	35.01	68.56	0.119	644.9

the value of the potentially lost quantity of outdoor activity (Gallagher and Smith 1985). If individuals were unable to substitute away from outdoor activities to mitigate risk, or if they lacked information on the risk in their area compensating surplus would be the correct measure (Gallagher and Smith 1985; Smith 1987; Foster and Just 1989). We assume they are informed by local health authorities and other information sources, so the correct measure is compensating variation (Freeman et al. 2014). Because the impacts of Lyme Disease and price are conflated in our empirical model we are only able to estimate the consumer surplus of a change in Lyme Disease. We observe point A in Fig. 1 with price $p_y(L)$, and our counterfactual is point B at the price of outdoor activity with no Lyme Disease, $p_y(0)$. The change in the price of outdoor recreation is $p_y(L) - p_y(0)$, and the impact of this change in price on demand is included in our regression $(\delta_1 \hat{L} + \delta_2 \hat{L}^2)$ where δ_1 and δ_2 contain the impact on quantity demanded from a change in the price due to a change in Lyme risk.

We estimate the monetary value of consumer surplus using values of time from the literature. However, standard methods require time substitution into labor, but our empirical work does not provide evidence of a shift towards labor. We conduct a welfare analysis that mirrors a travel cost model where the value of outdoor recreation is estimated by the amount individuals spend to travel to recreate outdoors relative to enjoying leisure at home (Freeman et al. 2014)—the location of the most indoor leisure.

There is a possibility that individuals are substituting a less preferred leisure activity in lieu of outdoor recreation. Assuming time not spent outdoors in the presence of Lyme is spent at home, then the travel time for the outdoor activity reveals a willingness to pay for the outdoor leisure activity beyond the willingness to pay for the home leisure activity. Thus, this forgone travel represents a non-money "income" or utility effect, and can be thought of as the additional travel time required to shift the budget curve from point A to point C in Fig. 1. This is an estimate of the income effect, and we can value this additional time at one third of the wage rate, the opportunity cost of leisure time commonly used in the literature (Cesario 1976; McConnell 1985).

4 Results

Model estimation results are shown in Table 2. The first column consists of an OLS regression with fixed effects for time and location and controlling for population. The second column includes controls for the attractiveness of the area, including minimum temperature and humidity as well as average precipitation. The third column uses additional available controls for the maximum humidity and temperature, as well as river and land area, the percentage of land that is wilderness of a municipal park, the percentage of land included in national parks and parks and recreation budgets. These controls were initially omitted due to concerns about their high correlation with other controls. The fourth column is the Arellano–Bond estimator treating cases as endogenous without controls except population, but including time fixed effects. The fifth column is the Arellano–Bond estimator with time fixed effects, mirroring column 2, including population, minimum humidity, minimum temperature, and precipitation (Roodman 2009).[13] A final regression, using system GMM and including all possible controls is included in column 6.

The OLS regression with controls and fixed effects (Table 2, column 1), has a negative and convex ($\delta_1 = -0.0499$ and $\delta_2 = 7.97 \times 10^{-5}$), but imprecisely estimated, relationship between outdoor activity and the number of Lyme Disease cases. The addition of controls for population, weather and the relative activeness of outdoor activity leads to a smaller effect ($-.0476$ and 7.88×10^{-5}) that is also imprecisely estimated (Table 2, column 2). Extending our set of controls to include all available information (column 3) does not improve the precision of our estimates, and we fail to reject a null of a relationship between outdoor time and cases at all standard significance levels. The insignificant coefficients on cases are not surprising, however, because Lyme cases in a particular year should follow time spent on outdoor activity in that year, counteracting any adaptive response.

We find precisely estimated, negative relationships between Lyme cases and outdoor recreation under the Arellano–Bond specifications (Columns 4 through 6 of Table 2), which account for endogenous covariates. The p values for the F-statistics for all three Arellano–Bond specifications suggest that the models fit the data. The Hansen tests suggest that our set of instruments is exogenous, and we fail to reject the null the Arellano–Bond test for autocorrelation in the second lag, which provides further support for the exogeneity of our instruments.[14] The estimates for the main parameters of interest are consistent across the three Arellano–Bond specifications. This consistency is maintained for the specification with the full control set (Column 6) across multiple robustness checks (Appendix Table 2), discussed below. This leads us to prefer the full set of control specification. The parameter estimates from the specifications with fewer controls, Columns 4 and 5, are within the 95% confidence interval of the full control specification, Column 6. Furthermore, all three specifications suggest a convex relationship, which implies that marginal impact of additional cases has a diminishing effect on the adaptive response – each additional case elicits a smaller marginal response.

[13] All Arellano–Bond models use orthogonal deviations for cases as instruments, as well as a measure of the predicted tick habitat in that geography as an additional instrument for Lyme cases.

[14] The vast majority of infectious disease models are either first-order differential or difference equations models or first-order Markov models. Therefore, theory suggests that we would not expect correlation in the errors to persist for greater than one time period.

Table 2 Parameter estimate (standard errors) for outdoor activities located away from home

	(1) OLS FE	(2) OLS Lim	(3) OLS	(4) Arellano–Bond	(5) Arellano–Bond	(6) Arellano–Bond
Lyme cases	−0.0499	−0.0476	−0.0473	−0.0262**	−0.0234**	−0.0248**
	(0.0311)	(0.0322)	(0.0324)	(0.0106)	(0.0097)	(0.0100)
Lyme cases squared	$7.97 \times 10 - 5$*	7.88×10^{-5}*	7.86×10^{-5}	5.20×10^{-5}**	4.49×10^{-5}**	4.67×10^{-5}**
	(4.68×10^{-5})	(4.79×10^{-5})	(4.80×10^{-5})	(2.27×10^{-5})	(2.25×10^{-5})	(2.25×10^{-5})
Population	1.48×10^{-6}	-4.79×10^{-7}	-3.98×10^{-7}	-4.59×10^{-8}	2.12×10^{-7}*	4.12×10^{-7}
	(1.54×10^{-5})	(1.64×10^{-5})	(1.65×10^{-5})	(1.24×10^{-7})	(1.21×10^{-7})	(2.81×10^{-7})
Min humidity		0.0380	0.0709		0.114	0.251
		(0.2323)	(0.4726)		(0.173)	(0.420)
Min temperature, F		0.0095	0.0835		−0.467**	−0.756
		(0.3391)	(1.060)		(0.199)	(0.585)
Precipitation (inches)		0.1666	0.138		−0.307	−0.315
		(2.162)	(2.171)		(0.417)	(0.574)
% Wilderness			−1.765			0.2590
			(27.833)			(3.03)
% City parks			3.005			0.0659
			(11.286)			(0.8840)
Max humidity			-7.21×10^{-3}			−0.184
			(0.330)			(0.279)
Max temperature, F			0.090			0.229
			(1.153)			(0.623)

Table 2 continued

	(1) OLS FE	(2) OLS Lim	(3) OLS	(4) Arellano–Bond	(5) Arellano–Bond	(6) Arellano–Bond
River area			−88.609			4.441
			(377.553)			(5.574)
Land area			1.90×10^{-9}			-2.30×10^{-10}
			(1.55×10^{-8})			(2.53×10^{-10})
% Nat parks			0.947			0.5240
			(5.317)			(1.068)
Parks rec			0.037			−0.0071
			(.065)			(0.012)
Lagged minutes of outdoor recreation				−0.0215	−0.0644***	−0.0672***
				(0.0362)	(0.0212)	(0.0223)
Year fixed effects		X	X	X	X	X
Location fixed effects	X	X	X			
Constant				6.947***	29.03*	37.65
				(1.62)	(17.10)	(25.49)
N	845	845	845	670	670	670
Hansen				1.00	0.766	0.953
Arellano Bond AR(1) test				0.008	0.009	0.009
Arellano Bond AR(2) test				0.433	0.195	0.2
Adjusted R-squared	0.0330	0.0339	0.0295			
F-statistic p values	0.0943	0.0974	0.1302	0.022	<0.001	0.001

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Using the Column 6's specification the average individual is expected to spend 1.54 fewer minutes per day outdoors at the average of 72.168 cases in a geography. For context slightly more than 56% of respondents in the dataset spend less than 1.54 min on outdoor activity per day. Our estimate is comparable to behavioral responses to the 2009 A/H1N1 pandemic (Bayham et al. 2015). At its peak, the 2009 A/H1N1 pandemic had a peak of 9,734 new national cases per week, and the average individual spent 22.11 additional minutes at home (Bayham et al. 2015). In our study a geography in the 90th percentile of CDC confirmed Lyme Disease cases has 226.8 cases per year, and individuals to spend a total of 3.22 fewer minutes per day outdoors. However, responses to A/H1N1 were short-lived, while the response to Lyme is persistent over a longer period.

If individuals performed more recreational activity in the last period than normal, they are likely to spend less time in the current period, and vice versa. For each additional hour spent on outdoor activity in the previous year, individuals spend 4.03 fewer minutes outdoors in the current year (coefficient of 0.0672 with p value 0.003). This is suggestive of habit formation and reversion to a mean level of activity over the long term.

4.1 Robustness Check

We estimate several alternative specifications to evaluate the robustness of the results. First, we expand the activities considered to include those taking place close to and away from home, shown in Table 3 in the appendix. This was done by including all activities that took place at the activity location code for one's own backyard. With this larger sample the point estimate is precisely estimated and the effect size is negative and of a similar order of magnitude to the base dataset for our preferred specification and the no control specification, but the relationship between case numbers and outdoor activity is not precisely estimated in our limited controls specification (Table 4). This is evidence that individuals are consistent in their risk mitigation activities over different areas when controlling for the variation in neighborhood recreation opportunities.

Next, we use activities away from home partitioned into weekends only and weekdays only. When partitioning the data set to only activity on weekends and weekdays we lose statistical power, 620 and 619 observations respectively. For our preferred specification the estimates are less precisely estimated (p values around 0.1), but the point estimates are of a consistent sign and magnitude (Table 4). The limited control set does not provide consistent estimates across datasets, and the estimates with no controls cease to be precisely estimated.

5 Opportunity Cost of Lyme Disease

We calculate the impact of living in a world with Lyme Disease risk, relative to the case where the ecosystem disservice were eliminated, by using our parameter estimates to find the reduced time spent on outdoor activities, and calculating the welfare cost using the most probable alternative uses of that recreational time. Guided by theory, we know that in a riskier world individuals are unable to attain the same utility level without a compensating shift in their time budget.

We map the average lost minutes of outdoor recreation for the northeastern United States from 2003 to 2012 by county based on the model predictions from our preferred specification (Fig. 2). The largest impacts of Lyme Disease on lost outdoors time is focused in three general areas. The first is centered around Boston, Massachusetts, the second around New York City and parts of New Jersey and Connecticut, and finally around Baltimore and Washington, D.C. There are also small loci of lost outdoor activity near Minneapolis and Chicago. These high lost levels of activity result from a juxtaposition of a large number of people and a high number of Lyme Disease cases.

Using our parameter estimates from our preferred specification, we find that the average individual in an average geography spent 1.54 fewer minutes outside per day in response to an average of 72.17 CDC confirmed Lyme cases in their geography. In our study area an average of 1.54 fewer minutes of outdoor activity per day is equivalent to 564.5 min, 9.41 h, less of outdoor activity per year. In aggregate 206 million days of outdoor leisure are lost per year assuming a day of outdoor leisure is 6 h long.[15] Alternatively, the average length of an outdoor activity in the ATUS data is 73.21 min, implying 7.71 forgone outdoor trips per person or 1.01 billion lost trips.

If we assume individuals respond only by spending less time outdoors (i.e., the time vanishes so this is a pure income effect), we calculate the welfare impact by using the intertemporal elasticity of labor supply. We use 2006 USD as our numeraire because 2006 is the midpoint of the data series. Prior literature has estimated the value of leisure time of \$11.27–12.06/h in 1992 USD or \$16.19–\$17.33/h in 2006 USD (Larson et al. 2004; Larson and Shaikh 2004). Using the estimated values of leisure time from Larson and Shaikh (2004) and Larson et al. (2004) provides estimates of \$20 billion and \$21.4 billion (in 2006 USD) annually.

Assuming that individuals are substituting to indoor recreational activity that takes place at home, a more reasonable assumption supported by the ATUS data, we can use the willingness to travel as a measure of WTP for outdoor activity. In the ATUS dataset we observe the amount of time individuals spend traveling before and after outdoor activities, enabling us to exploit this information for a travel cost approach.[16] Individuals in our dataset on average spend 1 min travelling for every 1.92 min of outdoor activity, resulting in an average of 292.48 min of travel time per year. If individuals do not enjoy travel time, then this is a cost that they face to participate in outdoor activity, and reflects a willingness to pay to substitute away from indoor activity. We value this time at a fraction of the wage rate, as is traditionally done in the recreation demand literature (Larson and Shaikh 2004; Phaneuf and Smith 2005). We assume individuals work 2080 h a year (40 h a week for 52 weeks) and use the median household income reported in "Income earnings and poverty data from 2006 American Communities Survey" of \$48,451 (Webster and Bishaw 2007) and calculate a mean income of ATUS respondents of \$32,012 for annual wages of \$23.29 and \$13.00 respectively.[17] One third of these wage rates (Cesario 1976) are \$7.76 and \$4.33 per hour respectively, suggesting an aggregate willingness to pay for Lyme-free outdoor opportunities of \$4.97 and \$2.77 billion per year respectively. It is important to note that when the substitution effect is included the welfare impacts of Lyme Disease are an order of magnitude smaller. Individuals are able to substitute away from the risky activity into other recreation activities. Taking into account this change can significantly reduce welfare effects when close substitutes are available.

Our welfare estimates correspond well to the broader recreation demand literature. The average length of an outdoor activity in the ATUS data is 73.21 min long implying that the average individual took 7.71 few outdoor trips per year due to Lyme Disease risk per year. Our travel cost approach implies that outdoor trips were valued at \$2.74 to \$4.91 per trip,

[15] Siderelis and Smith (2013) use an average stay length of 3 h in state parks. Using their estimate, we find an aggregate of 412 million days were lost.

[16] To our knowledge this is the first time this information in the ATUS has been used for travel cost analysis.

[17] The income variable in the ATUS is categorical, so we assume individuals work 2,080 h per year (40 h a week for 52 weeks) and use a weighted average of the income variable. While the ATUS is a stratified random sample of US households, the strata are not on income, and the survey maybe oversampling lower income households.

which is consistent with values commonly found in the literature (McConnell 1985; Phaneuf and Smith 2005).

6 Conclusions

Individuals respond to risk by investing in costly self-protection or self-insurance (Shogren and Crocker 1999). We found that individuals spent less time on outdoor recreation, and likely more time indoors and away from ticks in response to Lyme Disease. Our risk response, 1.54 fewer minutes outside per 72.17 CDC confirmed Lyme cases, is comparable with the average per case response to the 2009 A/H1N1 (aka swine flu) pandemic. This is likely due to the local and persistent nature of Lyme Disease as well as the nature of the activities we are studying. While the swine flu pandemic statistic was nationwide, individuals in our study are responding to a local risk that is persistent.

Substitution effects play an important role in valuing the welfare losses from risk in non-market activities. While we can clearly measure the substitution from outdoor recreation, without an accompanying way to measure the income effect, we cannot provide reliable estimates of the welfare effects of diminished nature-based leisure services. Measuring the income effects is difficult and requires that the opportunity cost of an activity takes place in such a way that it is observable and measurable.[18] This is vital to avoid conflating our measured risk avoidance behavior, the substitution from outdoor recreation, with a welfare effect. In our study, this welfare effect is the shift in the time budget that would leave individuals just as well off as if they moved from a riskless world to a risky world. We cannot easily measure this effect because individuals appear to shift from one leisure activity to another leisure activity in our sample. Without a clear way to estimate the value of that second leisure activity, we rely on the current methods in the literature of valuing time.

Ecosystems can provide both services (e.g., outdoor recreation) and disservices (e.g., refuge for infectious diseases). Increased Lyme Disease risk is important because individuals find themselves worse off, unless they have readily available and perfect substitutes for affected leisure activities. The true costs of any good or bad are the related opportunity costs. This is as true of infectious disease and environmental disservices as any other good or bad produced. Lost recreation expenditures are clearly not true economic costs. Our research suggests that individuals are capable of engaging in avoidance behavior by reducing one leisure activity and engaging in another. The welfare effects of such substitution are uncertain, however recognizing that human adaptive behavior is driven by the goal of reducing utility losses, and that lost outdoor recreation time is not a complete loss changes our welfare estimates by an order of magnitude. Our research highlights important economic-ecology features of Lyme Disease and also illustrates the care needed when valuing ecosystem services and dis-services.

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[18] There are issues with estimating the exact welfare loss due to the availability of substitutes that are also leisure activities. We suspect this is common in the literature where seemingly dissimilar alternative leisure activities are not considered as substitutes (e.g., nature-based outdoor activities and indoor activities).

Appendix

See Tables 3 and 4.

Table 3 Activities in analysis, limited to those taking place outdoors and away from home

Activity code		Activity name
130	102	Playing baseball
130	103	Playing basketball
130	104	Biking
130	108	Climbing, spelunking, caving
130	110	Equestrian sports
130	112	Fishing
130	113	Playing football
130	114	Golfing
130	116	Hiking
130	118	Hunting
130	120	Playing racquet sports
130	123	Playing rugby
130	124	Running
130	126	Playing soccer
130	127	Softball
130	130	Playing volleyball
130	131	Walking
130	199	Playing sports
130	202	Watching baseball
130	203	Watching basketball
130	204	Watching biking
130	210	Watching equestrian sports
130	212	Watching fishing
130	213	Watching football
130	214	Watching golfing
130	218	Watching racquet sports
130	221	Watching rugby
130	222	Watching running
130	224	Watching soccer
130	225	Watching softball
130	227	Watching volleyball
130	228	Watching walking
130	299	Attending sporting events
130	301	Waiting related to playing sports or exercising
130	302	Waiting related to attending sporting events
130	399	Waiting associated with sports, exercise and recreation
130	401	Security related to playing sports
130	402	Security related to watching sports
139	999	Sports, exercise and recreation not included

Table 4 Robustness checks for the Arellano–Bond GMM specification, parameter estimates and p values

	Model	Confirmed Lyme cases	p value	Confirmed Lyme cases squared	p value	Hansen test	Arellano Bond AR1 test	Arellano Bond AR2 test	F-statistic p value
Base model	No controls	−0.026	0.016	5.20×10^{-5}	0.024	1.0	0.008	0.433	0.022
	Limited controls	−0.023	0.018	4.49×10^{-5}	0.049	0.766	0.009	0.195	<0.001
	Full controls	−0.025	0.015	4.67×10^{-5}	0.041	0.953	0.009	0.2	0.001
Located away and at-home	No controls	−0.028	0.018	5.52×10^{-5}	<0.001	1.0	0.005	0.307	0.141
	Limited controls	−0.055	0.999	9.08×10^{-5}	0.998	<0.001	0.999	1.0	1.0
	Full controls	−0.026	0.021	4.86×10^{-5}	0.053	0.93	0.006	0.143	0.043
Weekends	No controls	0.031	0.561	9.49×10^{-5}	0.895	<0.001	0.009	0.084	<0.001
	Limited controls	−0.008	1.0	5.20×10^{-5}	0.99	<0.001	0.987	0.987	0.997
	Full controls	−0.03	0.108	7.28×10^{-5}	0.014	0.904	0.009	0.055	0.022
Weekdays	No controls	−0.013	0.319	3.80×10^{-5}	0.268	1.0	0.034	0.264	<0.001
	Limited controls	−0.016	1.0	3.69×10^{-5}	0.99	<0.001	0.011	0.0	1.0
	Full controls	−0.022	0.096	4.91×10^{-5}	<0.001	0.923	0.038	0.646	0.054

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