Intertemporal Substitution and the Value of Leisure Time*

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Abstract

Understanding the extent to which people substitute activities across time is important for evaluating behavior and welfare impacts in many contexts including assessing the damages caused by oil spills and climate change impacts. We develop a structural demand model that explicitly focuses on intertemporal substitution and incorporates time constraints on behavior. We also implement a flexible, individualized approach to measuring how people value their leisure time and how substitutable time is between periods. The model is estimated in an empirical application using data on recreation demand. The results demonstrate how getting the value of time 'right' is important for assessing welfare impacts of policies with large intertemporal substitution effects. We find people value their leisure time heterogeneously and substantially differently from their implied wage rate and this value differs by time of year. These findings raise concerns with the common practice of only using labor market information to value people's leisure time.

Keywords: Intertemporal substitution, Value of time, Demand system

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Individuals' ability to intertemporally substitute activities has significant implications in a number of areas of economic decision-making, including transportation choices (Davis, 2008; Arnott et al., 1993), labor supply decisions (Connolly, 2008; Shi and Skuterud, 2015), averting behavior related to pollution (Graff Zivin and Neidell, 2014), time-use decisions (Castro et al., 2012), leisure travel (Van Nostrand et al., 2013), and recreational activities (Smith and Palmquist, 1994; Hartmann, 2006; Kuriyama and Hanemann, 2006). Regulations and events often impact the temporal availability and quality of these activities. Laws restrict the consumption of some goods such as alcohol to certain times of day (Boyes and Faith, 1993). Drivers respond temporally to congestion and time-of-use road charges (Hess et al., 2007). Leisure activities such as fishing and hunting are rationed using season restrictions. Oil spills and other adverse environmental events may lead to temporary closures of recreation areas. Climate change is expected to shorten the season length for winter activities such as skiing and extend the season length for some summer activities such as beach visits and golf (Mendelsohn and Markowski, 1999; Shaw and Loomis, 2008). In all these contexts, understanding how individuals substitute activities across time is critical to anticipating behavioral responses and accurately assessing costs and benefits.

Modeling how individuals allocate activities across time is closely related to how individuals value their time. Estimates for the value of time (VOT) are important for a wide range of areas in the academic literature and policy applications including transportation (Small and Verhoef, 2007), the value of a statistical life (Ashenfelter and Greenstone, 2004), monetary economics (Karni, 1973; Mulligan, 1997), understanding lifecycle consumption patterns and patterns of non-market work over the business cycle (Aguiar and Hurst, 2007; Aguiar et al., 2013), recreation demand (Phaneuf and Smith, 2005), and policy evaluation (Calfee and Winston, 1998;

Bento et al., 2009). The VOT is especially pertinent for travel cost demand models because they use the costs of a trip to a site as implicit prices to evaluate behavior and welfare. While there is a large literature illustrating how demand forecasts and welfare estimates can vary depending on the VOT used (e.g., Fezzi et al., 2014), there is no consensus on the most appropriate approach to valuing time (Palmquist et al., 2010). By far the most common approach is to utilize some fraction of the hourly wage rate calculated from household income questions (Parsons, 2003). While this approach is grounded in the theory of the leisure-labor tradeoff, it faces a number of issues such as practical challenges in converting self-reported household income measures to hourly wage estimates, accommodating people outside the labor market, and the questionable assumption that leisure time is valued at a fixed proportion of the wage across broad cross-sections.

The assumption that the individual VOT is stable over a given temporal interval may be suspect as well. The VOT can vary depending on the time of day (Tseng and Verhoef, 2008), the amount of time available (Palmquist et al., 2010), and may vary seasonally within a year if leisure time is not perfectly fungible. The presence of household or employment constraints can limit the ability of individuals to trade leisure days at different times of years. For example, households with children may only be able to take family vacations during scheduled school breaks and employers may implicitly or explicitly limit employees' ability to take their vacation days at will. Furthermore, the structure of the traditional work schedule, with its fixed weekends and holidays, may limit fungibility as well. These predetermined leisure days typically vastly outnumber discretionary vacation days, where the individual can choose the timing.[1] Taken together, these

[1] For example, assuming a 5 day work week and 10 days of vacation a year, the ratio of weekend days to vacation days is around 10 to 1. While vacation days provide individuals the opportunity to allocate days off when they are most valuable, the average number of paid vacation days per worker in the United States is only 10 (Ray et al.,

reasons for the lack of fungibility of leisure time suggest that the VOT may depend on the time of year.

In this paper, we develop and implement a structural demand model that explicitly focuses on intertemporal substitution. We start from a static Kuhn-Tucker (KT) model which provides a utility-consistent framework for modeling decisions at both the extensive (what good to consume) and intensive (how much of a good) margins while also allowing for zero consumption levels (i.e. corner solutions) in a unified setting (Phaneuf et al., 2000; von Haefen et al., 2004; Bhat, 2008). We incorporate temporal considerations in two ways. First, we recast the choice set from 'what good to consume' to 'when to consume', allowing us to study intertemporal substitution patterns within the robust substitution framework inherent in the random utility model (RUM). Second, we relax the assumption that all leisure time can be allocated anytime, and is therefore valued equally across season, by implicitly incorporating seasonal leisure time constraints. Most demand models simply collapse the time constraint into the budget constraint under the assumption that time can be traded off against money at a constant rate - a practice that has been challenged theoretically and empirically (Shaikh and Larson, 2003; Castro et al., 2012).

We also allow flexibility in how individuals value their leisure time, rather than assuming that heterogeneity across individuals in their valuation of leisure time arises solely through variation in their wage. We use responses to money-time and leisure-season trade-off questions and estimate individual-specific VOT estimates that embed a substantial amount of both observed and unobserved constraint heterogeneity such as employment status and family life, as well as heterogeneity based on individual characteristics such as income and alternative uses of time.

2013), over a quarter of American workers do not receive paid time off (Bureau of Labor Statistics, 2015), and around 50 percent of available paid time is not taken on average (Glassdoor, 2014).

We estimate the model using revealed and stated preference data from recreational anglers in the U.S. Gulf of Mexico (GOM). Comparing our individual-specific VOT estimates to the conventional measures, we find that the average individual-specific VOT is around 70 percent of hourly income, significantly larger than the one-third of wage rule of thumb typically implemented in the literature. More importantly, the correlation between the two estimates is small, suggesting that people value their leisure time quite differently than what their labor market returns imply. Furthermore, we find evidence of a substantial seasonal variation in the VOT. The implications for welfare impacts can be significant. Using the individual-specific approach to valuing time results in 51 to 68 percent higher welfare measures for policies with large intertemporal substitution effects but only small differences for policies with small intertemporal substitution opportunities. Thus, getting the VOT 'right' is important for assessing impacts of policies or exogenous shocks with potentially large intertemporal substitution effects.

1. Relevant Literature

1.1. Modeling Temporal Substitution

This paper contributes to the literature on how people choose to allocate activities across time.[2] Economists studying recreation demand have utilized and developed a wide range of models to address substitution across (typically spatial) choice alternatives within a temporal interval. However, modeling to incorporate substitution behavior *across* time is comparatively limited (Phaneuf and Smith, 2005). Existing models that incorporate temporal considerations in recreation demand models fall into two classes: fully and partially dynamic choice models. The primary difference is that partially dynamic models are solely "backward looking" in considering

[2] In this paper, we directly address two temporal research needs identified by Phaneuf and Smith (2005) in their review chapter on recreation demand models: "the role of inter-temporal constraints (and opportunities) in individual choice" and "the opportunity cost of time".

the implications of past decisions for current welfare, whereas fully dynamic models are "forward looking" in that they allow individuals to consider the implications of their current decisions on future welfare and decision making.

Fully dynamic models include the rational habit formation model (Adamowicz, 1994), and dynamic programming models within a random utility maximization (RUM) framework (Provencher and Bishop, 1997; Baerenklau and Provencher, 2005). Estimation complications with fully dynamic models have led to assumptions that substantially reduce the practical usefulness of these types of models, which largely explains the lack of widespread adoption in the literature (Phaneuf and Smith, 2005; Swait et al., 2004).

The much more prevalent approach to including temporal dimensions in choice models is the use of partially dynamic recreational models because they are simpler to estimate and can easily incorporate a wide range of preference heterogeneity. These models commonly employ a repeated static RUM specification, where individuals are assumed to repeatedly make decisions of whether to take a trip to one of the recreation sites or stay home. Temporal effects can be incorporated in three different ways. First, state dependence effects across choice occasions can be incorporated through the use of variables measuring the total number of (consecutive) times a given option was chosen (Moeltner and Englin, 2004; Boxall and Englin, 2008). Second, temporal correlation and substitution patterns across choice occasions can be included through the use of repeated random parameters logit models with error components (Herriges and Phaneuf, 2002). Third, the choice set can be recast from an individual choosing different sites to choosing different time periods to take a trip as in Swait et al. (2004) and Carson et al. (2009). The main finding from these partially dynamic studies is that past experience with recreation sites matters in estimation and welfare results.

There are four main challenges associated with the use of repeated discrete choice models in a temporal context. First, the researcher needs to specify the number of choice occasions that each person faces. The usual approach is to use the same number for all individuals and set it equal to the maximum number of trips in the dataset. While Lupi (2005) has shown that the trip prediction and welfare measures are invariant to the number of choice occasions, it is not clear that these results hold if there are a heterogeneous number of choice occasions.[3] The second issue is the role of the error terms in these models. The most common specification of the repeated discrete choice models is the repeated nested logit model. Each choice occasion is modelled independently, not only across individuals but also across choice occasions, which explicitly excludes the possibility of intertemporal substitution.[4] More flexible models such as random parameters logit models can capture cross choice occasion correlation patterns but place a large burden on the error terms in accounting for substitution, preference heterogeneity and all other unobserved drivers of choices. Disentangling these different roles is difficult. Third, repeated discrete choice models assume a constant marginal utility from taking trips in a period and do not incorporate satiation effects (Bockstael and McConnell, 2007). Finally, repeated discrete choice models focus on the decision process at the choice occasion of what site to choose, and no consensus has emerged on how to consistently link these individual choice occasions to decisions made over the season (von Haefen and Phaneuf, 2005).

The KT model used in this paper explicitly addresses each of these challenges. The structural econometric framework jointly models both extensive (when to take a trip) and intensive (how

[3] For example, long distance tourists may only make the decision to visit a specific beach once a year, whereas local residents may make weekly beach visit decisions. These differences in the number of choice occasions may be confounded with preference heterogeneity if the same number of choice occasions are used for each individual in the modeling.

[4] For example, English et al. (2015) used a repeated nested logit model to estimate the lost recreational use from the Deepwater Horizon oil spill.

many trips to take) choice margins in a utility-consistent framework. No decisions on the number of choice occasions need to be made. Substitution patterns are captured through utility parameters rather than relying on unobserved error terms that also characterize unobserved preference heterogeneity. Furthermore, KT models relax the assumption of constant marginal utility of trips, utilizing choice behavior to estimate the rate of satiation.[5]

1.2. The Valuation of Time

This paper also contributes to the VOT literature by providing a flexible approach to computing individual-specific VOT estimates that allows heterogeneity in how people value their time while also allowing seasonal variability in the VOT. Estimates of the VOT are especially pertinent for travel cost demand models because in addition to monetary costs of travelling to a site, all travel cost models require assumptions regarding how people value their leisure time. Since Cesario and Knetsch (1970) illustrated the biases to welfare estimates of recreation trips from excluding time costs, there has been controversy in how to value leisure travel time. By far the most common practice is based on the labor-leisure trade-off and uses income information to value time. This approach is theoretically grounded in the time allocation framework of Becker (1965) and assumes that time can be transferred freely between leisure and work, implying that the monetary value in labor can be used to value leisure time. In practice, this income-based

[5] Kuriyama and Hanemann (2006) modify the static KT model by extending the choice set to include multiple periods. However, their model specification does not include any time constraints and assumes that the individual cannot adjust the numeraire good across periods which limits intertemporal substitution. It is perhaps not surprising that their empirical results suggest that there are relatively small differences in the in-sample trip predictions and welfare estimates if these intertemporal considerations are ignored.

approach almost always uses a constant fraction of the hourly wage rate computed from self-reported income.[6]

While using a constant fraction of the wage rate is the most common practice, there are some complications associated with this approach. Converting self-reported household income measures to an hourly wage estimates raises a number of issues including whether to use household or personal income, how to handle non-wage income, and assumptions on the number of hours worked. Furthermore, wages may be a poor proxy for VOT for people that are outside the formal labor market such as the unemployed, the retired or students. Implicitly the income-based measures value their time at zero. More fundamentally, the income-based approach to valuing time imposes the arbitrary assumption that all leisure time is valued at a fixed proportion of the wage.

Some alternative approaches to valuing time better reflect time's lack of fungibility. Smith et al. (1983) consider two different types of time constraints in a household production model for recreation decisions. The first is a long-run constraint where individuals divide time between labor, recreation and non-recreation activities. The second constraint is short-run in nature where individuals allocate their recreation time between alternative sites. The theoretical model illustrates the interrelationship between an individual's time constraints and the corresponding VOT, and the authors suggest collecting detailed data on the nature of individual time constraints. Feather and Shaw (1999) use a two-equation labor supply model to estimate a shadow VOT that reflects the fact that not all individuals can smoothly trade-off work time for leisure time. For flexibly employed workers, the shadow value equals the market wage, but is

[6] English et al. (2015) reviewed 65 recreation demand studies that used a value for travel time, and around 50 percent used 1/3 of hourly income. The majority of the remaining studies used either zero values or the full amount of hourly income.

less than (more than) the market wage for under-employed and unemployed (over-employed). Palmquist et al. (2010) note that the shadow VOT may differ depending on the time horizon considered and propose a hierarchical decision structure. They combine the long run shadow VOT estimates from the Feather and Shaw (1999) approach with responses to short-run time/money trade-off questions in a stated preference survey to estimate the marginal value of weekly recreational time.[7] The specific time-money trade-off question was structured as options to purchase a personal assistance service for household maintenance activities such as yard work/gardening and running errands. Palmquist et al. (2010) find that the short-run marginal value of recreational time increases as trip lengths extend from 2 to 8 hours.

Other revealed preference contexts for valuing time that do not directly rely on income are road tolls and driving behavior. Fezzi et al. (2014) estimate the value of travel time using data on the decisions to take toll roads that save time compared to slower free roads to beaches in Italy. While noting substantial observed and unobserved heterogeneity, they estimate a mean VOT between 50 and 70 percent of household income. The advantage of this approach is that it uses actual decisions in a recreation context, but it is limited in its applicability since toll roads are not common in many parts of the world and the approach may suffer from omitted variable bias (Wolff, 2014). Wolff (2014) analyzes hourly driving speed decisions as a function of gasoline prices and finds that a one-dollar increase in the price of gas per gallon decreases speed by 0.27 miles per hour. Using this relationship, the VOT is calculated to be 50 percent of the gross wage rate.

[7] Casey et al. (1995) and Ovaskainen et al. (2012) provide two other examples of the use of stated preference questions to elicit the VOT in a recreation context.

While most applications employ a relatively simple measure of the VOT there is ample evidence that the VOT is heterogeneous and may not align with the standard 1/3 of the wage rate assumption. Furthermore, there are both theoretical arguments (DeSerpa, 1971) and empirical evidence (Tseng and Verhoef, 2008; Palmquist et al., 2010) that the VOT may differ depending on context. In this paper, we implement an approach to valuing time that incorporates a substantial amount of observed and unobserved heterogeneity while also allowing the VOT to differ by season.

2. Conceptual Model

We modify the traditional static KT model (Bhat 2008, von Haefen and Phaneuf 2005) in two ways to incorporate temporal considerations. First, we redefine the choice as how many trips to take within different time periods, rather than focusing on the locations of trips as in most standard recreation demand models.[8] This re-framing of the choice set allows us to study intertemporal substitution patterns similarly to spatial substitution in RUMs. Second, we extend the constraint set of the KT model to include season-specific, individual-specific leisure time constraints as well as a monetary budget constraint to reflect the fact that leisure time may not be perfectly substitutable across time periods.

With these modifications, we can outline the conceptual model that underlies the empirical analysis. We take the work-leisure trade-off, and thus income, as given; assume a certain number of fixed leisure days in each (sub-annual) period; and assume the total number of vacation days can be considered exogenous variables. Each individual is assumed to maximize annual utility through choice of recreation days and non-recreation leisure days in each time period and a

[8] This recasting of the choice set from sites to time periods is similar to the nested logit specification in Carson et al. (2009).

numeraire good over the entire year, subject to a monetary budget constraint, an annual constraint on vacation days, and a constraint on available leisure time for each time period. Individuals face the following problem[9]:

$$\max_{r_t, l_t, v_t, x} \sum_{t=1}^{T} U(r_t, l_t, Q_t, x)$$

Subject to

$$y = \sum_{t=1}^{T} r_t c_t + x,$$
$$\sum_{t=1}^{T} v_t = H, \text{ and}$$
$$L_t + v_t = r_t + l_t.$$

where:

r_t is the number of recreation days,

l_t is the number of non-recreation leisure days,

Q_t is a vector of quality characteristics for recreation,

x is the numeraire good with price normalized to one,

y is annual income,

c_t is the monetary cost of a recreation day,

v_t is the number of discretionary vacation days,

H is the total annual number of available vacation days, and

L_t is the total number of fixed leisure days such as weekends/holidays.

Appendix A provides the Lagrangian for the optimization problem and resulting first-order conditions. The KT conditions that implicitly define the optimal number of recreation trips to take in time period t are given by:

[9] We ignore discounting between time periods (i.e. the discount factor equals one).

$$\frac{U_{r_t}}{U_x} \leq c_t + \frac{\mu_t}{\lambda}, \qquad t = 1, \dots T, \tag{1}$$

$$r_t \left[\frac{U_{r_t}}{U_x} - c_t - \frac{\mu_t}{\lambda}\right] = 0, \qquad t = 1, \dots T.$$

where μ_t is the Lagrangian multiplier associated with the leisure time budget constraint in period t, and λ is the Lagrangian multiplier associated with the monetary budget constraint. The left hand side of the first equation is the Marshallian "virtual price" of r_t while the travel cost on the right hand side is composed of the monetary out of pocket costs, c_t, and the time-specific opportunity cost of a leisure day, μ_t/λ. For time periods with a positive number of recreation trips, the virtual price and travel cost are equalized. If no recreation trips are taken in a given time period, then the virtual price is bounded from above by the travel cost. The first-order conditions from the conceptual model provide estimating equations for the empirical analysis.

If fixed leisure days L_t were fungible across time periods (as are vacation days in this conceptual model) then individuals would be free to allocate this leisure time, along with vacation days, throughout the year to equalize the opportunity cost of a leisure day (i.e. $\mu_t/\lambda = \mu/\lambda$ for all t). However, there are ample reasons why this might not hold in reality. Fixed seasonal leisure days impose a positive upper bound on leisure time in periods when less leisure may actually be desired. The model predicts that no discretionary vacation time will be taken in these periods with surplus leisure and that the marginal VOT will be less in these periods than those in which vacation time is consumed.

While not explicitly included in the conceptual model, limitations on the ability to reallocate vacation time across seasons may lead to cases in which vacation time is utilized in all periods and yet the opportunity cost of leisure is not equalized across periods. For example, if an individual faces pressure at work not to take too much vacation in a month, then they may be

unable to equalize the value of leisure across periods. Similarly, an individual making decisions about family leisure decisions may be limited in their ability to arbitrage their allocation of vacation days due to spousal labor constraints, school schedules, etc.

3. Empirical Application and Data

The empirical application is an evaluation of a policy change that involves potential intertemporal reallocation of recreational headboat fishing trips in the U.S. Gulf of Mexico (GOM).[10] While anglers on headboat trips fish for a variety of species, two of the most important target species for marine recreational fishing in this region are red snapper and gag grouper, both of which are managed by federal fishery regulations. The recreational fishery for these species can be considered regulated open access (Homans and Wilen 1997) with nominal state license fees, aggregate catch limits, bag and size limits, and season lengths. There are, however, no direct limits on the number of angler trips during the season. As a result of increased fishing pressure, the fishing season for red snapper in GOM federal waters has decreased substantially from around 200 days in the early 2000s to only 42 days in 2013 and 9 days in 2014. Gag grouper has followed a similar, yet somewhat muted, pattern, with fishing seasons down to five or six months in recent years.[11]

[10] A headboat is a vessel licensed to carry groups of 15 or more passengers on recreational fishing trips in the exclusive economic zone of the US GOM (Gulf of Mexico Fishery Management Council, 2016). Headboats (also called party boats), charter boats, and guide boats are different types of for-hire fishing vessels participating in GOM marine recreational fishing. For more background on the fishery, see Abbott and Willard (2016).

[11] Starting in 2014, the regulator, the National Oceanic and Atmospheric Administration (NOAA) Fisheries, issued an exempted fishing permit for two years to the GOM Headboat Collaborative. This pilot program used an allocation based management strategy and, instead of being constrained by short fishing seasons, the Collaborative was allocated a fixed quota of red snapper and gag grouper that could be caught anytime of the year. Thus, in 2014 and 2015 for the first time in almost 20 years, recreational anglers could fish for these target fish species year-round. A total of 19 vessels from various ports in the GOM participated in the program. The current paper is part of a broader research project that aims to evaluate the pilot program, including the benefits to recreational headboat anglers of a more flexible fishing season (Abbott and Willard, 2016).

Survey Design and Structure

We developed an online survey to collect information on the behavior and preferences of headboat anglers in the GOM. To evaluate the survey and ensure that questions were interpreted correctly, we conducted two focus groups with local anglers in Pensacola, Florida in August 2015. We pre-tested the online version of the survey in October 2015 with a subset of the sample to update the experimental designs and to ensure there were no technical issues.[12]

The survey consists of six sections. The first section includes questions on the respondent's vacation behavior, familiarity with the GOM, as well as general recreation questions. Detailed recall questions on the number and characteristics of headboat trips the respondent took in the previous year are included in the second section. A key aspect of the survey is that trip information is collected for both partial (4 to 8 hours) and full (8 to 15 hours) day trips for each of four different time periods: Winter/Spring (January to May), June, Summer (July to August), and Fall (September to December).[13]

The third section includes two contingent behavior questions where respondents indicated the number of partial and full day trips they would have taken in the previous year under alternative fishery management regimes with varying fishing season lengths, bag limits for the target species, and prices per partial and full day headboat trip.[14] The first contingent behavior question (Policy A) always included a "status quo" restricted fishing season (June for red snapper, July to

[12] Of the 200 individuals invited by email to participate in the pre-test, 39 surveys were completed. The full survey instrument is available from the authors upon request. The order of Sections 3, 4 and 5 was randomized to account for possible ordering effects.

[13] June is given its own time period because it is the month in recent years when red snapper is allowed to be retained.

[14] The target species was either red snapper or gag grouper depending on what part of the GOM the respondent went fishing. Respondents had an 80 percent chance of receiving the gag grouper survey version (20 percent chance of red snapper version) if they took a headboat trip from Southwest Florida. All other respondents had an 80 percent chance of receiving the red snapper survey version.

December for gag grouper), with a bag limit of 2, but various headboat trip prices. The second question (Policy B) allowed year round fishing for the target species, a bag limit of 1, 2, or 3, and various headboat trip prices. The headboat trip price levels were $50/$80, $80/$130, $120/$200, and $150/$250 for partial/full day trips. An example of a contingent behavior question is provided in Figure B1 in Appendix B.

The fourth section includes a trip choice experiment that is not the focus of the current study. The fifth section includes the leisure time valuation questions. Respondents were presented with two choice scenarios asking them to sacrifice time for a monetary payment to either participate in a focus group or complete a short-term contract sorting paper files. Both willingness-to-accept (WTA) scenarios were for 8 hours near the respondent's home during one of their days off in the three summer months (June, July and August).[15] The choice question used a stochastic payment card (SPC) approach which combines a payment card with polychotomous choice responses. The SPC approach is closely related to the multiple-bound discrete choice (MBDC) approach but allows respondents to use a combination of words and numerical values to more easily express their preferences and uncertainty (Wang and Whittington, 2005).[16] The main advantage of the SPC approach in our context is that it efficiently gathers substantial preference information per question for deriving individual specific estimates of the VOT. An example of the focus group question is presented in Figure B2 in Appendix B.

A set of leisure day trade-off questions were posed to calculate marginal rates of substitution (MRS) for leisure days throughout the year. Each respondent was presented with two questions with three alternatives each: two scenarios that changed the number of leisure days in the

[15] We used a WTA format instead of willingness-to-pay (WTP) because individuals are giving up their time to travel for recreation rather than buying their time.
[16] Other applications of the SPC approach are Bollino (2009) and Wang and He (2011).

summer, fall, and winter periods, and a no change option.[17] Respondents chose their most and least preferred options. Figure B3 in Appendix B presents an example of the leisure time trade-off question. The final section of the survey includes socio-demographic questions.

Survey Administration

We recruited anglers into the survey sample using respondents to an onboard survey deployed in 2014 and 2015 on headboat vessels that participated in the GOM Headboat Collaborative pilot program (see footnote 11). The onboard survey consisted of 20 questions that asked about their trip experience and collected some socio-demographic information. Furthermore, respondents had an option to provide their email address if they wanted to participate in the online survey.

We administered the survey in two waves for the 2014 and 2015 samples.[18] The first wave was conducted between December 2 and 22, 2015, while the second occurred between February 11, and March 7, 2016. A total of 823 respondents completed the online survey for a response rate of 15 percent, which was the same for both waves. A total of 2,439 observations from 813 respondents are included in the KT estimation as for each individual we have the recall data and two contingent behavior responses.[19] Table 1 provides summary statistics on select socio-demographic characteristics.

[17] To reduce cognitive burden for respondents, we only use three time periods to calculate the marginal rates of substitution: winter/spring (January to May), summer (June to August) and fall (September to December).

[18] To provide an incentive to complete the online survey, respondents were told that everyone who completes the survey will be entered into a drawing for a $100 Amazon gift card. The survey was programmed in Qualtrics. A total of three email reminders were sent to respondents that had not completed the survey. Of the 10,719 respondents who completed the onboard survey, 5,330 unique email addresses were provided (1,574 for 2014 and 3,756 for 2015) for an initial response rate of 50 percent.

[19] A further 573 individuals started the online survey but did not finish it, for a completion rate of 59 percent. The median time to finish the survey was 32 minutes. There were 10 completed surveys that were not included in the analysis for various reasons including 6 respondents with no valid US zip code for their home address, 2 respondents that did not indicate which site they visited and hence a travel cost model could not be estimated, 1

****Table 1 about here****

4. Empirical Model and Analysis

4.1 Travel Costs

Before estimating the KT model, we first compute the costs of a fishing trip (e.g., travel costs) at the individual-level which includes the headboat trip fees as well as the costs of travelling to the GOM. For each individual, we calculate travel costs using both nonmonetary opportunity costs of time (μ_t/λ) and monetary cost information (c_t). We use two different VOT approaches to determine travel costs. The first approach ($\text{VOT}_{1/3\text{wage}}$) follows the most common practice in the literature and assumes each individual values their time at 1/3 of their hourly income regardless of time of year. The second approach allows heterogeneity and seasonality in how people value their time. This individual-specific, seasonal VOT approach (VOT_{ISS}) consists of three steps. First, using responses to the time-money WTA questions for the three summer months (June, July, and August), we estimate a random parameters logit model including both observed heterogeneity through socio-demographic characteristics and unobserved heterogeneity through random parameters (Revelt and Train, 1996).[20] Using the model parameter estimates, for each individual we obtain a distribution of VOT estimates for summer months, conditioned on the individual's observed choices and socio-demographic characteristics. The mean of the conditional distribution for each individual is then simulated to derive an individual-specific VOT estimate (Hensher et al., 2015). Second, an additional random parameters logit model is

respondent that only visited a port outside of the Collaborative program, and 1 respondent who indicated they took 290 headboat trips a year.

[20] Socio-demographic characteristics are incorporated as affecting the means of the random parameters and include employment status (working full or part-time, self-employed, or not working), a dummy variable whether the respondent is male, education level (some college or less, a bachelor's/associate's degree, or a graduate degree), a dummy variable if the respondent's household income is above $100,000, household size, a dummy variable for whether the respondent has children, and the age index variable.

estimated using responses to the seasonal leisure trade-off questions to derive individual-specific MRS estimates of a summer day for fall and winter days. Third, these MRS values are used to rescale the summer VOT estimates to yield three VOT_{ISS} estimates per person: Winter (January to May), June/Summer (June to August), and Fall (September to December). While the VOT_{ISS} metric varies across seasons, we also calculate a single individual-specific time-constant average VOT (VOT_{ISTC}) measure for each individual for comparison to the $VOT_{1/3wage}$ measure.[21] Appendix C provides more details on the two approaches to estimating the VOT for each individual.

To capture the monetary costs of travel, we develop an expected travel cost model to account for the fact that some individuals travel long distances to go fishing in the GOM (Industrial Economics, 2015; Leggett, 2015). If we followed the common practice in the travel cost literature of assuming all individuals travel by car (such that travel costs are a linear function of distance), these costs may be overestimated if individuals took a cheaper mode of travel when long distances are involved, such as flying. We estimate expected travel costs by calculating a weighted average of these driving and flying costs, where the weights are the probabilities of choosing each mode of travel. The probability of flying increases as the travel distance increases and is based on actual mode choices from the 2009 National Household Travel Survey (NHTS). The main implication of the expected travel cost model is that travel costs are a nonlinear function of distance due to the large fixed costs associated with air travel (i.e. costs per-mile decreases as the total distance travelled increases). The details of the expected travel cost

[21] To calculate the individual-specific time-constant VOT for each individual, we use a weighted average of the seasonal VOT estimates from the individual-specific approach, where the weights are the number of months in the different time periods.

calculations are provided in Appendix C. Table 2 provides a summary of the key data sources used in the empirical analysis.

****Table 2 about here****

4.2 Kuhn-Tucker Model

Once travel costs have been calculated, we use the first-order conditions from the conceptual model as the estimating equations in the empirical analysis. These first-order conditions along with distributional assumptions for unobserved heterogeneity provide the likelihoods for estimation. To operationalize the model, we need to define the preference specification for utility. We use the translated generalized constant elasticity of substitution (tCES) utility function (Bhat, 2008), which is closely related to the linear expenditure system (LES) used in the environmental economics literature (von Haefen and Phaneuf, 2005). This function is additively separable across fishing trips in different time periods as well as between fishing trips and the numeraire good. We assume additive separability of utility between fishing trips (r_t) and non-fishing leisure time (l_t) which allows non-fishing leisure time to be included in the numeraire good term. The specific functional form is

$$U(r_t, Q_t, x) = \sum_{t=1}^{T} \frac{\gamma_t}{\alpha_t} \psi_t \left[\left(\frac{r_t}{\gamma_t} + 1 \right)^{\alpha_t} - 1 \right] + \frac{\psi_0}{\alpha_0} x^{\alpha_0} \tag{2}$$

where $\gamma_t \geq 0$ and $\alpha_t, \alpha_0 \leq 1$ for all t are required for this function to be consistent with the properties of a utility function (Bhat, 2008). Bhat (2008) provides a thorough overview of the interpretation of these parameters. In brief, ψ_t is the marginal utility of a trip in period t when $r_t =$

0, α_t controls the rate of diminishing marginal utility of additional recreation trips in a certain time period, and γ_t translates the underlying indifference curves which allows for corner solutions (i.e. zero trips in a certain time period). Weak complementarity, the condition that individuals do not receive utility from a good if they do not consume it (Maler, 1974; Smith and Banzhaf, 2004), is imposed in this specification by adding and subtracting a one inside the square brackets of (2). In our application, T=8 as we have a total of 8 fishing trip alternatives as respondents can take partial and full day trips in 4 different time periods.

The baseline marginal utility of a trip ψ_t for each trip type and time period is parameterized as an exponential function of trip quality variables Q_t to ensure $\psi_t > 0$. ψ_t also includes multiplicative omitted heterogeneity by individual and choice alternative so that $\psi_t(Q_t,\varepsilon_t) = \exp(\beta Q_t + \varepsilon_t)$. We include observed heterogeneity by interacting individual-specific variables with the quality variables, with the numeraire good serving as the base.[22]

There are a number of identification concerns in KT models that must be addressed before estimation. First, Bhat (2008) describes how γ_t and α_t both influence the quantity of good t consumed through their impact on satiation effects, such that it is difficult to disentangle these two effects. We restrict the satiation parameter to be constant across all goods ($\alpha_t = \alpha_0 = \alpha$) while allowing the translation parameter (γ_t) to vary across alternatives. Furthermore, as in other applications of the KT model (e.g. Bhat, 2008), we restrict the α parameter to be between 0 and 1 for convergence considerations. Finally, we estimate separate scale parameters for the recall and contingent behavior data to account for any differences in the variances of the error terms.

[22] Specifically, the ψ_0 parameter for the outside good is specified as $\psi_0 = \exp(\varepsilon_0)$.

Another unique aspect of the KT model compared to the linear-in-income discrete choice model is the role of the income constraint. In KT models, total costs on all trips and the numeraire good must add up to income. Most applications of the KT model have used only monetary income (e.g. von Haefen and Phaneuf, 2005). Larson and Shaikh (2001) illustrate the inconsistency in using a time price in recreation models with only monetary income. A practical issue with only using monetary income is that for low-income individuals, the opportunity costs of time embedded in travel costs could cause total trip costs to exceed income. We construct a total income measure for each individual that includes both monetary and leisure income to better reflect the total resources available to an individual. Leisure income is calculated using the season-specific VOT estimates for each individual and the amount of leisure time available in each time period.[23]

To better show the connection between the conceptual model described above and the empirical model, we can substitute the total income budget constraint for the numeraire good into Equation (2). The total income budget constraint consists of monetary and leisure income and subtracts the expenditure spent on fishing trips, $p_t r_t$, where p_t is the full virtual price of each trip type consisting of both monetary and time costs ($p_t = c_t + \mu_t/\lambda$). Making this substitution yields

$$U(r_t, Q_t, x) = \sum_{t=1}^{T} \frac{\gamma_t}{\alpha_t} \psi_t \left[\left(\frac{r_t}{\gamma_t} + 1 \right)^{\alpha_t} - 1 \right] + \frac{\psi_0}{\alpha_0} \left(y + \sum_{t=1}^{T} \frac{\mu_t}{\lambda} (v_t + L_t) - \sum_{t=1}^{T} p_t r_t \right)^{\alpha_0}.$$

Using the KT conditions in Equation (1) and the utility function specified in Equation (2), Appendix A derives the following estimating equations:

[23] While the VOT_{ISS} approach uses the season-specific VOT estimates, the income-based approach uses the same value for all time periods. We assume that for each month, there are 64 leisure hours available (8 days x 8 hours per day). We also estimated the models with only monetary income and the welfare results are quite similar to the total income specification. The intuition for this result is that while excluding leisure income has the expected income effect on welfare estimates, a larger budget share is now spent on fishing, increasing the preference parameters for fishing trips and causing welfare estimates to increase.

$$V_t + \varepsilon_t = V_0 + \varepsilon_0 \qquad \text{if } r_t^* > 0\text{, and}$$

$$V_t + \varepsilon_t < V_0 + \varepsilon_0 \qquad \text{if } r_t^* = 0\text{, where}$$

$$V_t = \beta' Q_t + (\alpha - 1) ln\left(\frac{r_t}{\gamma_t} + 1\right) - \ln(p_t)$$

$$V_0 = (\alpha - 1) ln(x)$$

To complete the econometric model structure we assume the ε error terms for an individual are distributed according to a type 1 extreme value distribution that is independent between individuals, trip types and seasons (t), and choice occasions in the survey.

There are three additional complications that require modification to the estimation approach. First, because we are using estimated VOT variables in our travel cost calculation for the individual-specific approach, we need to account for this additional source of uncertainty in the standard errors.[24] Using the individual conditional distributions from the VOT and leisure trade-off choice models, we sample 400 vectors of the estimates of the VOT across each season and individual. We then estimate the KT model using each of these vectors. The second complication is that the recall data and the responses to the two contingent behavior questions create a total of three sets of observations per respondent. To account for the potential correlation in preferences across responses for the same individuals, we use the clustered bootstrap approach to subsume the correlation in preferences in the parameters of the model (Cameron and Miller, 2015). To implement this approach, we draw with replacement, a weighted (see below) sample of 813 individuals from our dataset and estimate the model using the block of all three observations per individual. This bootstrapping procedure is repeated 400 different times in combination with the 400 distinct VOT estimates. The final complication is that individuals who completed the online

[24] Lew and Larson (2005) illustrate the importance of accounting for the stochastic nature of the VOT in recreation demand modeling.

survey may differ from individuals in the general headboat angler population. To help address potential issues of stratification and self-selection, we use a two-stage strategy to construct survey weights.[25] These weights are used to define the probability of an individual being sampled in the bootstrap procedure.

4.3 Trip Prediction and Welfare Analysis

Once we estimate the KT model to recover parameters of the utility function, we use a simulation-based approach for welfare measurement and trip prediction. We define the Hicksian compensating surplus (CS^H) for a change in price and quality from baseline levels p^0 and Q^0 to new levels p^1 and Q^1 using the expenditure function as

$$CS^H = y - e(p^1, Q^1, U^0, \theta, \varepsilon), \tag{3}$$

where θ is the vector of structural parameters (ψ_t, α, γ_t) and $U^0 = V(p^0, Q^0, y, \theta, \varepsilon)$. Two complications arise in solving for CS^H. First, $e(.)$ depends on both interior and corner solutions for the underlying Hicksian demands in the T time period/trip length combinations and is an endogenous regime-switching function. Second, the ε's in CS^H are unknown to the researcher, making CS^H a random variable (von Haefen and Phaneuf, 2005).

We use Monte Carlo integration techniques to simulate multiple realizations of the errors and calculate the CS^H conditional on each simulated value. There are two steps to constructing the

[25] The first stage aims to ensure the spatial and temporal distribution of our sample reflects the headboat angler population. We use logbook data from all headboat vessels in the GOM to calculate the percentage of anglers in each of the four seasonal periods and GOM regions (Texas, Alabama, Northwest Florida, Southwest Florida). We then compute spatial-temporal post-stratification survey weights. The second stage addresses non-response bias, where non-response includes failure to provide an email on the 2-page onboard survey or failure to complete the internet survey, by using data on characteristics from those individuals who completed the onboard survey (see Appendix B), but did not complete the online survey. We weight individuals using estimated propensity scores using the following characteristics: gender, age, income, number of years fishing, how often an individual goes fishing, and where the individual lives. Weights from the two stages are multiplied together and normalized such that the sum equals the sample size.

Hicksian compensating surplus measures. In the first step we simulate unobserved heterogeneity, and the second step uses the KT model to predict how anglers respond following changes to prices, site closures, or other quality changes (von Haefen and Phaneuf, 2005). For the first step, we use the conditional approach to drawing error terms such that the KT model perfectly predicts the trip decisions of anglers for periods with positive trips (von Haefen and Phaneuf, 2005).[26]

Once the errors have been simulated, the structural model is used to predict behavior under baseline and counterfactual conditions as well as the change in welfare. Deriving Hicksian demands for welfare analysis using KT models is typically complicated and the currently available methods are either enumerative (Phaneuf et al., 2000) or iterative (von Haefen et al., 2004). These procedures can be time-intensive, and we require a more efficient approach to incorporate model parameter uncertainty.[27] As a solution, we use a recently developed approach described in Lloyd-Smith (2017) that extends Pinjari and Bhat's (2011) Marshallian demand forecasting routine to simulate Hicksian demands suitable for welfare analysis. This substantially improves computational speed because it allows for closed-form welfare simulations. Lloyd-Smith (2017) provides the analytical details for the extended routine. We use the conditional approach for welfare measurement using 500 independent sets of error draws for each individual.

For trip prediction, we follow Abbott and Fenichel (2013) and use Pinjari and Bhat's (2011) demand forecast approach to simulate Marshallian demand. We use the unconditional approach

[26] For time periods/trip types where trips are zero, the errors are simulated from a type I extreme value distribution that has been truncated to reflect this choice. Thus the conditional approach uses observed behavior by individuals to characterize unobserved heterogeneity.

[27] To incorporate parameter uncertainty, we repeat the error simulations and demand predictions for each realization of the model parameters generated by each of the 400 bootstraps. Thus, for the 400 bootstrap iterations over 813 observations and 500 error realizations, we need 1.63×10^8 demand simulations for each policy.

for trip predictions to evaluate the in-sample fit of model specifications using the root mean squared error (RMSE) metric and to examine substitution behavior.[28]

5. Results

We present three sets of results. First, we compare the individual-specific and income-based VOT estimates and show the implications for overall travel costs. Second, we present the KT model results using the two VOT approaches and the trip prediction metrics. Lastly, we present the behavioral substitution and welfare implications for three different policy scenarios.

5.1 Value of Time

We first compare the individual-specific VOT estimates using responses from the time valuation questions to the more traditionally used income based VOT measures.[29] Using the individual-specific approach, we calculate the individual-specific time-constant VOT (VOT_{ISTC}) to be \$27 (median \$23) with a range of \$6 to \$96. Using the income-based approach, the average hourly equivalent wage of respondents is \$39 (median \$34) with a range of \$0 to \$429. Comparing averages, the VOT_{ISTC} measure is around 70 percent of the average hourly wage, which is comparable to the results in Palmquist et al. (2010). The convention in the recreation demand literature is to use 1/3 of computed hourly wages, which yields an average $VOT_{1/3wage}$ estimate of \$13. Figure 1 shows a scatterplot of the relationship between the VOT_{ISTC} and $VOT_{1/3wage}$ estimates for each individual along a 45-degree line. There is only a weak positive relationship

[28] The unconditional approach uses unconditional draws from the entire distribution of unobserved heterogeneity. We use the unconditional approach for trip prediction as it does not make sense to use the conditional approach because errors are drawn such that trips are perfectly predicted. The root mean squared error is calculated over the recall data only and uses the actual trips taken by anglers and the predicted Marshallian demands from the KT model.

[29] The individual-specific estimates are calculated as the mean of the conditional distribution of the VOT using observed choices and socio-demographic characteristics. The detailed derivation of these measures at the individual level is explained in Appendix C.

between the two estimates (ρ =0.14).[30] Furthermore, a large number of unemployed or retired individuals are imputed a $0 VOT using the income-based approach, yet their choice behavior reveals a positive valuation.[31]

****Figure 1 about here****

5.2 Marginal Rate of Substitution of Leisure

Next, we present the results on the marginal rate of substitution of fall ($MRS_{f,s}$) and winter ($MRS_{w,s}$) days for a summer day which are used to calculate the seasonal variation in the VOT. The individual-specific estimates for $MRS_{f,s}$ range from 0.29 to 1.59 with a mean of 0.65 whereas the $MRS_{w,s}$ ranges from 0.23 to 1.67 with a mean of 0.64. Figure 2 presents the distribution of individual-specific estimates of MRS for all respondents. If all leisure time throughout the year were valued the same, then the MRS would equal one. Values less than one imply that people value summer days more than fall/winter days while values greater than one suggest the opposite. These results suggest that people do in fact value leisure time differently depending on the season – although at the population level the opportunity cost of time in the fall vs. winter relative to the summer is quite similar – and there is a substantial degree of heterogeneity.

****Figure 2 about here****

5.3 Travel Costs

[30] If we only include employed individuals, the correlation coefficient is 0.22.
[31] Appendix D presents a set of robustness checks on our individual-specific VOT approach; results from these checks support the validity of the approach used in this paper.

The preceding results show that there are differences in the VOT estimates between the two approaches. To summarise the effects of the two VOT estimates on travel costs, we compare the time portion of travel costs to the monetary costs. The average time costs per trip using the income-based approach are $390, or $130 if 1/3 of this amount is used. This compares to an average of $274 per trip using the VOT_{ISS} approach. Total monetary costs are composed of headboat trip fees, which average $145, and costs associated with traveling to the port such as gas, accommodation, and airfare, which average $135 per trip. The correlation of overall travel cost (including time costs) utilizing the two alternative approaches to time valuation is 0.69. Consequently, we conclude that the time portion of travel costs is a significant component of overall travel costs and differences between the income-based and individual-specific VOT approaches may have consequences for modeling.

5.4 Estimation

Table 3 reports parameter estimates for the KT model using the two alternative travel cost measures. Model 1 uses the individual-specific, seasonal (VOT_{ISS}) approach while Model 2 uses the conventional 1/3 wage income-based ($VOT_{1/3wage}$) approach. The estimated average log-likelihood at convergence of Model 2 is less than that of Model 1 suggesting the VOT_{ISS} specification fits the data better. The in-sample trip prediction metrics also report a slight improvement using the VOT_{ISS} specification. Nevertheless, both likelihood criteria and in-sample fit suggest that the improvements from utilizing the VOT_{ISS} approach are relatively modest.

****Table 3 about here****

The model coefficients are quite similar between the two VOT specifications except for the June and Summer time period dummy variables, which are higher in Model 1. Holding other quality

variables and travel costs constant, full day trips are preferred to partial day trips for people who have a home in the GOM but not for people visiting from further away. Trips in June and Summer time periods are more preferred to other times of year in general, but older individuals prefer the Winter and Fall periods. The interpretation of the positive and significant coefficient for the contingent behavior dummy variable is not straightforward because the larger estimated scale parameter for the recall responses dampens this effect.[32] The retain fish variable captures whether red snapper or gag grouper could be kept by the angler once caught in the certain time period and has the expected positive sign.[33] For socio-demographic variables, individuals with children are less likely to take headboat trips in general but are more likely in the summer months when school is out of session. The translation parameters (γ_t) influence the rate of satiation and the propensity toward corner (zero) solutions for a given trip type and season. In general, the greater the value of γ_t the less an individual satiates on that choice and the less likely they will choose zero trips. However, these parameters are difficult to directly compare because the time periods have a different number of months. Thus, while the larger values of the translation parameters for Winter and Fall time periods seemingly reflect lower satiation for these time periods, on a per-month basis, June actually has the lowest rate of satiation – not surprisingly given that this is the month where the red snapper season is typically open. The scale parameter estimates suggest that the variance in the recall responses is greater than the variance in the contingent behavior data.

[32] A common finding in recreation demand modeling is to find more trips taken in the contingent behavior scenario compared to the recall scenario (Englin and Cameron, 1997). In our data, the average annual number of trips per individual is 3.56 in the recall scenario and 3.65 in the contingent behavior scenarios. As a robustness check, we also estimate both models using only the recall data. The parameter estimates are similar to the models presented in the paper using both recall and contingent behavior data and the welfare impacts are slightly higher. This result gives us more confidence that the contingent behavior dummy variable and heterogeneous scale parameters are appropriately controlling for any systematic differences between the recall and contingent behavior data.

[33] For the recall responses, we used the respondent's knowledge of the GOM Headboat Collaborative pilot program to code the retain variable as either year round if they knew about the program, or only for time periods that align with the traditional target species (either red snapper or gag grouper) season if they did not know about the program.

5.5 Substitution and Welfare Analysis

To simulate behavioral responses and welfare impacts, we use the actual trip data for each individual as the baseline, where the average annual number of trips per angler is 3.6 and mean total trip expenditures are $1,024. We compare three policy scenarios that differ in the degree to which they bear upon intertemporal substitution possibilities:

- Policy 1: an increase in per trip prices of $25/$50 for partial/full day trips;
- Policy 2: closure of all fishing in the Summer time period; and
- Policy 3: closure of all fishing in the Fall time period.

Because Policy 1 consists of relatively small price increases (4 to 9 percent) across all time periods, incentives for intertemporal substitution should be limited. Policies 2 and 3 concern possible hypothetical temporary closures of the GOM recreational fishery caused by events such as an oil spill or the regulatory environment in response to overharvesting. As an example, on April 20, 2010, an explosion on the drill rig Deepwater Horizon led to the closure of much of the GOM fishery for that summer.[34] The seasonal closures of Policies 2 and 3 should generate more substitution of trips across time.

Before discussing welfare impacts, we first present the behavioral substitution responses to the two seasonal closure policies. Figure 3 illustrates the mean percentage change in expenditures on fishing trips in the different periods as well as the numeraire for the two models. Starting with the intensive margin changes between trips in different time periods, Model 1 predicts larger

[34] The damage assessment for the Deepwater Horizon Oil Spill estimated that the welfare losses associated with recreational uses totalled $660 million (English et al., 2015).

percent changes in expenditures than Model 2. The KT specification, while still somewhat constrained by its additively separable structure, relaxes the independence of irrelevant alternatives (IIA) assumption embedded in type I extreme-value discrete choice models within the model parameters, rather than through the error structure (Vasquez Lavin and Hanemann, 2008). Indeed, the substitution patterns suggest small deviations from proportionate shifts in expenditures across seasons. Examining the extensive margin change, the percentage increase in numeraire expenditure is relatively modest, because fishing trip expenses are small part of total expenditures for the majority of individuals. However, the percentage decrease in total trip expenditures is estimated to be -17 percent (Model 2) to -19 percent (Model 1) under Policy 2 and -22 percent (Model 2) to -23 percent (Model 1) under Policy 3.

****Figure 3 about here****

Table 4 reports annual Hicksian welfare estimates per anglers for the three policy scenarios using three alternative methods for calculating the VOT. We first discuss Model 1 and Model 2 and then introduce Model 3. For Policy 1, the welfare impacts are quite similar between the two models, with slightly higher estimates using Model 1 (-$128) compared to Model 2 (-$126). These initial results suggest that for policies with small intertemporal substitution possibilities, the specific VOT estimate may not matter much.

****Table 4 about here****

However, there is a large divergence between the model results for fishery closures, Policy 2 and 3. The summer fishing closure in Policy 2 results in a 68 percent larger welfare impact (-$501 versus -$298) using the VOT_{ISS} estimates compared to the $VOT_{1/3wage}$ approach. This difference in welfare estimates for the fall closure scenario is 51 percent (-$428 versus -$284), with the VOT_{ISS}

estimates again yielding larger impacts. Thus, for policies with large intertemporal substitution effects, the two VOT approaches lead to sizeable differences in welfare impacts, with the conventional income-based approach underestimating these impacts.[35]

Furthermore, the seasonal variation in the VOT also has implications for the welfare impacts of closures in different times of year. For Model 1, which allows for seasonality in the VOT, the summer fishing closures have a 17 percent larger welfare impact compared to the closure in the fall in part because of the higher VOT, on average, in the summer. These results suggest the timing of the fishing closure matters for welfare. Conversely, for Model 2, which uses a time-constant, wage-based VOT, closures in the summer have only a statistically indistinguishable 5 percent greater welfare impact than in the fall, suggesting the timing of the closure does not matter.

However, there are two key differences between the VOT measures for Model 1 and Model 2: flexibility in how people value their time and seasonal variation. To isolate the impacts for welfare estimates of allowing seasonality in the VOT we also estimate the KT model and simulate welfare impacts using the individual-specific, but time constant VOT that does not include any seasonal variation in the VOT (VOT_{ISTC}). Model 3 provides the welfare results for this model. The estimated mean welfare impact is -$422 for a summer closure compared to -$448 for a fall closure. Comparing these impacts to Models 1 and 2, it is clear that incorporating flexibility in how people value their time is critical for closing the gap between these two models, and is a larger factor in welfare impacts compared to temporal heterogeneity.

35 The welfare estimates are derived using the different parameter estimates from the two models as well as using the different VOT measures in the welfare calculations. We can decompose the role these two drivers have on the welfare estimates by simulating welfare measures using Model 1's parameter estimates and the $VOT_{1/3wage}$ measures and vice versa with Model 2's parameter estimates and VOT_{ISS} measures. Appendix E illustrates that the differences in welfare estimates are largely driven by differences in the VOT measures used to simulate welfare rather than differences in the estimated preference parameters across the two models.

Nevertheless, incorporating seasonality in the VOT has important implications for determining how the timing of the closure matters for welfare.

6. Conclusion

In this paper, we develop a structural demand model that places intertemporal substitution at its core. We also compare two alternative approaches to valuing time: a flexible approach that incorporates individual heterogeneity and seasonality, and the conventional income-based approach. We implement the model using revealed and stated preference data from an online survey of recreational anglers in the GOM. We find that the individual-specific VOT is around 70 percent of hourly income, which is larger than the value of 1/3 of hourly income that has dominated applications. More importantly, the correlation between the two estimates is small, suggesting that people value their time quite differently than what their labor market returns imply – implying that an income-based approach may suffer from serious measurement error. Furthermore, we find evidence of a substantial seasonal variation in the VOT. For welfare impacts, using the more flexible approach to valuing time results in 51 to 68 percent higher welfare measures for policies with large intertemporal substitution effects but only small differences for policies with small intertemporal substitution opportunities. Thus, getting the VOT 'right' is important for assessing impacts of events or policies with large potential intertemporal substitution effects such as oil spills, climate change impacts, or firm or government policies to temporally ration goods or services.

The research has two broader implications beyond modeling recreation demand. Our paper illustrates an approach to structurally modeling intertemporal substitution that is significantly more tractable than alternatives such as dynamic discrete choice models. The most common

approach of using repeated discrete choice models in contexts with significant intertemporal substitution may not be appropriate because these models ignore or largely downplay the role of intertemporal substitution in decision making. The KT model allows substitution patterns to be captured explicitly through utility parameters, incorporates satiation effects in each period, and jointly models consumption decisions along both the extensive and intensive margins. Our modeling also provides an illustration of how survey information can be used within the KT model structure to augment revealed preference data to better identify key parameters.

We contribute to the VOT literature by not only undermining the "1/3 wage" rule of thumb but by also revealing that the majority of individual-level differences in the VOT are not explained by reference to their return on the labor market. Even people who are disconnected from the labor market such as the unemployed or retired people do positively value their time. While our individual-specific approach implicitly assumes respondents are answering questions truthfully, the income-based approach also typically relies upon self-reported data. Thus the choice between approaches cannot rest on a preference for revealed preference data alone. As detailed in Appendix C, the income-based approach also requires a substantial number of assumptions to transform annual household income into an hourly wage metric. Furthermore, our more flexible approach does not preclude people from valuing their time using labor market returns. Another reason to move beyond the income-based approach is that it does not allow seasonal variation in the VOT. The results of this paper suggest that the VOT can differ depending on the season, and accounting for this variation is important for assessing welfare impacts of policies that cause intertemporal substitution of demand. Demand modeling is typically done at the individual level and thus requires valid information at this level. The flexible, individualized VOT approach used in this paper provides a useful means of obtaining this type of information. Adding a small

number of questions to a survey to elicit this information seems like a small price to pay. A valuable research agenda would be to investigate the heterogeneity in the VOT and its seasonal variation to better understand what individual characteristics drive these results.

REFERENCES

Abbott, J. K. and E. P. Fenichel. 2013. Anticipating adaptation: a mechanistic approach for linking policy and stock status to recreational angler behavior. *Canadian Journal of Fisheries and Aquatic Sciences 70*(8), 1190–1208.

Abbott, J. K. and D. Willard. 2016. Rights-Based Management for Recreational For-Hire Fisheries: Evidence from a Policy Trial. Arizona State University Working Paper.

Adamowicz, W. L. 1994. Habit formation and variety seeking in a discrete choice model of recreation demand. *Journal of Agricultural and Resource Economics 19*(1), 19–31.

Aguiar, M. and E. Hurst. 2007. Life-cycle prices and production. *The American Economic Review* 97(5): 1533-1559.

Aguiar, M., E. Hurst, and L. Karabarbounis. 2013. Time use during the great recession. *The American Economic Review* 103(5): 1664-1696.

American Automobile Association. 2015. 2015 Your Driving Costs. Technical report.

American Automobile Association. 2016. 2016 Your Driving Costs. Technical report.

American Hotel & Lodging Association. 2015. Lodging Industry Trends 2015. Technical report.

Arnott, R., A. de Palma, and R. Lindsey. 1993. A Structural Model of Peak-Period Congestion: A Traffic Bottleneck with Elastic Demand. *The American Economic Review 83*(1), 161–179.

Ashenfelter, O. and M. Greenstone. 2004. Using Mandated Speed Limits to Measure the Value of a Statistical Life. *Journal of Political Economy 112*(S1), S226–S267.

Baerenklau, K. A. and B. Provencher. 2005. Static modeling of dynamic recreation behavior: Implications for prediction and welfare estimation. *Journal of Environmental Economics and Management 50*(3), 617–636.

Becker, G. S. 1965. A Theory of the Allocation of Time. *The Economic Journal 75*(299), 493–517.

Bento, A. M., L. H. Goulder, M. R. Jacobsen, and R. Von Haefen. 2009. Distributional and Efficiency Impacts of Increased US Gasoline Taxes. *American Economic Review 99*(3), 667–699.

Bhat, C. R. 2008. The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological 42*(3), 274–303.

Bockstael, N. E. and K. E. McConnell. 2007. *Environmental and Resource Valuation with Revealed Preferences: A Theoretical Guide to Empirical Models*. Springer Science & Business Media.

Bollino, C. A. 2009. The Willingness to Pay for Renewable Energy Sources: The Case of Italy with Socio-demographic Determinants. *The Energy Journal 30*(2), 81–96.

Boxall, P. C. and J. E. Englin. 2008. Fire and recreational values in fire-prone forests: Exploring an intertemporal amenity function using pooled RP-SP data. *Journal of Agricultural and Resource Economics 33*(1), 19-33.

Boyes, W., and R. Faith. 1993. Temporal Regulation and Intertemporal Substitution: The Effect of Banning Alcohol at College Football Games. *Public Choice, 77*(3), 595-609.

Bureau of Labor Statistics. 2015. News Release USDL-14-1348. Technical report.

Calfee, J. and C. Winston. 1998. The value of automobile travel time: implications for congestion policy. *Journal of Public Economics 69*(1), 83–102.

Cameron, A. C. and D. L. Miller. 2015. A Practitioners Guide to Cluster-Robust Inference. *Journal of Human Resources 50*(2), 317–372.

Carson, R. T., W. M. Hanemann, and T. C. Wegge. 2009. A nested logit model of recreational fishing demand in Alaska. *Marine Resource Economics 24*(2), 101–129.

Casey, J. F., T. Vukina, and L. E. Danielson. 1995. The Economic Value of Hiking: Further Considerations of Opportunity Cost of Time In Recreational Demand Models. *Journal of Agricultural and Applied Economics 27*(02).

Castro, M., C. R. Bhat, R. M. Pendyala, and S. R. Jara-Daz. 2012. Accommodating multiple constraints in the multiple discrete-continuous extreme value (MDCEV) choice model. *Transportation Research Part B: Methodological 46*(6), 729–743.

Cesario, F. J. and J. L. Knetsch. 1970. Time Bias in Recreation Benefit Estimates. *Water Resources Research 6*(3), 700–704.

Connolly, M. 2008. Here Comes the Rain Again: Weather and the Intertemporal Substitution of Leisure. *Journal of Labor Economics 26*(1), 73–100.

Davis, L. 2008. The Effect of Driving Restrictions on Air Quality in Mexico City. *Journal of Political Economy 116*(1), 38–81.

DeSerpa, A. C. 1971. A Theory of the Economics of Time. *Economic Journal 81*(324), 828–46.

English, E., C. Leggett, and K. McConnell. 2015. Value of Travel Time and Income Imputation. NOAA Technical Memorandum E2. Technical report.

Feather, P. and W. D. Shaw. 1999. Estimating the cost of leisure time for recreation demand models. *Journal of Environmental Economics and Management 38*(1), 49–65.

Fezzi, C., I. J. Bateman, and S. Ferrini. 2014. Using revealed preferences to estimate the Value of Travel Time to recreation sites. *Journal of Environmental Economics and Management 67*(1), 58–70.

Glassdoor. 2014. Q1 2014 Employment Confidence Survey. Technical report.

Graff Zivin, J. and M. Neidell. 2014. Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics 32*(1), 1–26.

Gulf of Mexico Fishery Management Council. 2016. Reef Fish Recreational Management for Headboat Survey Vessels. Amendment 42 to the Fishery Management Plan for the Reef Fish Resources of the Gulf of Mexico. Technical report.

Hartmann, W. R. 2006. Intertemporal effects of consumption and their implications for demand elasticity estimates. *Quantitative Marketing and Economics 4*(4), 325–349.

Hensher, D., J. Rose, and W. Greene. 2015. *Applied Choice Analysis: A Primer* (2nd Edition ed). Cambridge, United Kingdom: Cambridge University Press.

Herriges, J. A. and D. J. Phaneuf. 2002. Inducing patterns of correlation and substitution in repeated logit models of recreation demand. *American Journal of Agricultural Economics 84*(4), 1076–1090.

Hess, S., J. W. Polak, A. Daly and G. Hyman. 2007. Flexible substitution patterns in models of mode and time of day choice: new evidence from the UK and the Netherlands. *Transportation* 34(2), 213–238.

Homans, F.R., and J.E. Wilen. 1997. A model of regulated open access resource use. *Journal of Environmental Economics and Management* 32(1): 1-21.

Industrial Economics, I. 2015. Air Travel Data Integration. NOAA Technical Memorandum E6. Technical report.

Kahle, D. and H. Wickham. 2013. ggmap: Spatial Visualization with ggplot2. *The R Journal 5*(1), 144–161.

Karni, E. 1973. The Transactions Demand for Cash: Incorporation of the Value of Time into the Inventory Approach. *Journal of Political Economy 81*(5), 1216–1225.

Kuriyama, K. and W. M. Hanemann. 2006. The intertemporal substitution of recreation demand: A dynamic Kuhn-Tucker model with a corner solution. Unpublished Manuscript.

Larson, D. M., S. L. Shaikh. 2001. Empirical Specification Requirements for Two-Constraint Models of Recreation Choice. *American Journal of Agricultural Economics* 83(2), 428–440.

Larson, D. M., S. L. Shaikh, and D. Layton. 2004. Revealing preferences for leisure time from stated preference data. *American Journal of Agricultural Economics 86*(2), 307–320.

Leggett, C. G. 2015. Technical Report: Travel Cost Computation. NOAA Technical Memorandum E1. Technical report.

Lew, D. K. and D. M. Larson. 2005. Accounting for stochastic shadow values of time in discrete-choice recreation demand models. *Journal of Environmental Economics and Management 50*(2), 341–361.

Lloyd-Smith, P. and W. L. Adamowicz. 2016. Can Stated Preference Measures of Willingness-to-Accept be Valid? Evidence from Laboratory Experiments. Resource Economics and Environmental Sociology Working Paper, University of Alberta.

Lloyd-Smith, P. 2017. A New Approach to Calculating Welfare Measures in Kuhn-Tucker Demand Models. Resource Economics and Environmental Sociology Working Paper, University of Alberta.

Lupi, F. 2005. Random Utility Models for Recreation Demand: Theory and Concepts for Welfare Measurement. Chapter Notes for AEC 891.

Mäler, K.G. 1974. *Environmental Economics: A Theoretical Inquiry*. Baltimore, MD, Johns Hopkins University Press for Resources for the Future.

Mendelsohn, R., and M. Markowski. 1999. The Impact of Climate Change on Outdoor Recreation. In *The Impact of Climate Change on the United States Economy*, edited by R. Mendelsohn and J.E. Neumann. Cambridge, UK: Cambridge University Press, 267–288.

Moeltner, K. and J. Englin. 2004. Choice behavior under time-variant quality. *Journal of Business & Economic Statistics 22*(2), 214–224.

Mulligan, C. 1997. Scale Economies, the Value of Time, and the Demand for Money: Longitudinal Evidence from Firms. *Journal of Political Economy 105*(5), 1061–1079.

Ovaskainen, V., M. Neuvonen, and E. Pouta. 2012. Modelling recreation demand with respondent-reported driving cost and stated cost of travel time: A Finnish case. *Journal of Forest Economics 18*(4), 303–317.

Palmquist, R. B., D. J. Phaneuf, and V. K. Smith. 2010. Short run constraints and the increasing marginal value of time in recreation. *Environmental and Resource Economics 46*(1), 19–41.

Parsons, G. R. 2003. The Travel Cost Model. In P. A. Champ, K. J. Boyle, and T. C. Brown (Eds.), *A Primer on Nonmarket Valuation*, Number 3 in The Economics of Non-Market Goods and Resources, pp. 269–329. Springer Netherlands.

Phaneuf, D. J., C. L. Kling, and J. A. Herriges. 2000. Estimation and Welfare Calculations in a Generalized Corner Solution Model with an Application to Recreation Demand. *Review of Economics and Statistics 82*(1), 83–92.

Phaneuf, D. J. and V. K. Smith. 2005. Chapter 15 Recreation Demand Models. In K.-G. M. a. J. R. Vincent (Ed.), *Handbook of Environmental Economics*, Volume 2 of *Valuing Environmental Changes*, pp. 671–761. Elsevier.

Pinjari, A. R. and C. R. Bhat. 2011. Computationally efficient forecasting procedures for Kuhn-Tucker consumer demand model systems: Application to residential energy consumption analysis.

Pollak, R. A. 1970. Habit Formation and Dynamic Demand Functions. *Journal of Political Economy 78*(4), 745–763.

Provencher, B. and R. C. Bishop. 1997. An estimable dynamic model of recreation behavior with an application to Great Lakes angling. *Journal of Environmental Economics and Management 33*(2), 107–127.

Ray, R., M. Sanes, and J. Schmitt. 2013. No-Vacation Nation Revisited. Technical report, Center for Economic and Policy Research.

Revelt, D., and K. Train. 1998. Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level. *Review of Economics and Statistics* 80, 647–657.

Rust, J. 1987. Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica 55*(5), 999–1033.

Shaikh, S.L. and D.M. Larson. 2003. A Two-Constraint Almost Ideal Demand Model of Recreation and Donations. *The Review of Economics and Statistics* 85(4), 953-961.

Shaw, W. D. and J. B. Loomis. 2008. Frameworks for analyzing the economic effects of climate change on outdoor recreation. *Climate Research 36*(3), 259–269.

Shi, J. and M. Skuterud. 2015. Gone Fishing! Reported Sickness Absenteeism and the Weather. *Economic Inquiry 53*(1), 388–405.

Small, K. A. and E. Verhoef. 2007. *The Economics of Urban Transportation* (2 ed.). New York, New York: Routledge.

Smith, M. D. 2005. State dependence and heterogeneity in fishing location choice. *Journal of Environmental Economics and Management 50*(2), 319–340.

Smith, V. K., and W. H. Desvousges, and M. P. McGivney. 1983. The opportunity cost of travel time in recreation demand models. *Land Economics 59*(3), 259–278.

Smith, V.K, and R.B. Palmquist. 1994. Temporal Substitution and the Recreational Value of Coastal Amenities. *The Review of Economics and Statistics* 76(1), 119-126.

Smith, V. K, and H. S. Banzhaf. 2004. A Diagrammatic Exposition of Weak Complementarity and the Willig Condition. *American Journal of Agricultural Economics, 86*(2), 455-466.

Swait, J., W. Adamowicz, and M. von Bueren. 2004. Choice and temporal welfare impacts: incorporating history into discrete choice models. *Journal of Environmental Economics and Management 47*(1), 94–116.

Tseng, Y.-Y. and E. Verhoef. 2008. Value of time by time of day: A stated-preference study. *Transportation Research Part B: Methodological 42*(7-8), 607–618.

Van Nostrand, C., V. Sivaraman, and A. R. Pinjari. 2013. Analysis of long-distance vacation travel demand in the United States: a multiple discrete-continuous choice framework. *Transportation 40*(1), 151–171.

Vasquez Lavin, F., and W.M. Hanemann. 2008. Functional Forms in Discrete/Continuous Choice Models with General Corner Solution. UC Berkeley, Department of Agricultural and Resource Economics, UCB.

von Haefen, R. H. and D. J. Phaneuf. 2005. Kuhn-Tucker Demand System Approaches to Non-Market Valuation. In R. Scarpa and A. Alberini (Eds.), *Applications of Simulation Methods in Environmental and Resource Economics*, pp. 135–157. Dordrecht: Springer Netherlands.

von Haefen, R. H., D. J. Phaneuf, and G. R. Parsons. 2004. Estimation and Welfare Analysis with Large Demand Systems. *Journal of Business & Economic Statistics 22*(2), 194–205.

Wang, H. and J. He. 2011. Estimating individual valuation distributions with multiple bounded discrete choice data. *Applied Economics 43*(21), 2641–2656.

Wang, H. and D. Whittington. 2005. Measuring individuals' valuation distributions using a stochastic payment card approach. *Ecological Economics 55*(2), 143–154.

Wolff, H. 2014. Value of time: Speeding behavior and gasoline prices. *Journal of Environmental Economics and Management 67*(1), 71–88.

Table 1: Socio-demographic summary statistics (N=813)

Variable	Description	Mean	Min	Max
Children	Dummy variable if children in home	0.34	0	1
Home in GOM	Dummy variable if live in GOM region	0.13	0	1
Fishing experience	GOM fishing experience (years / 10)	1.42	0	7.5
Angler organization	Dummy variable if part of angler org.	0.16	0	1
Male	Dummy variable if male	0.83	0	1
College Degree	Dummy variable if hold a college degree	0.57	0	1
Age	Age of respondent	50.6	18	84
Income	Annual Income ($000s)	105	15	275
Work full- or part-time	Dummy variable if working full- or part-time	0.63	0	1
Self-employed	Dummy variable if self-employed	0.10	0	1
Bachelor degree	Dummy variable if hold a bachelor degree	0.39	0	1
Graduate degree	Dummy variable if hold a graduate degree	0.18	0	1
Household size	Number of members in household	2.80	1	9

Table 2: Summary of Data Sources for Model Variables

Variable	Source
Trip Data (r_t)	Recall and contingent behavior survey questions
Monetary Travel Costs (c_t)	*Driving and Flying Costs*: Various sources, see Appendix C. *Fishing trip Fees*: Survey of boat operators.
Time Travel Costs (μ_t/λ)	*Income-Based Approach*: Income and hours worked survey questions. *Individual-Specific Approach*: Stochastic payment card question (Figure B2) and leisure day trade-off question (Figure B3).

Table 3: Parameter Estimates for Kuhn Tucker Model

	Model 1: Individual-specific, seasonal value of time (VOT_{ISS})		Model 2: Income-based value of time ($VOT_{1/3wage}$)	
	Estimate	*z*-stat	Estimate	*z*-stat
Marginal utility of trip parameters (ψ_t)				
Constant	-7.05	-25.92	-6.89	-24.52
Full day trip	0.00	-0.02	0.01	0.06
Winter	-0.48	-2.31	-0.41	-1.91
June	1.36	5.81	1.14	4.78
Summer	1.25	4.67	0.99	3.48
Contingent behavior	0.48	9.85	0.52	10.63
Retain fish	0.16	2.54	0.17	2.52
Retain fish*Red snapper	0.00	0.00	-0.01	-0.16
Children	-0.34	-3.28	-0.42	-3.92
Children*Summer	0.28	2.42	0.30	2.64
Fishing experience	0.04	1.26	0.06	1.67
Angler organization	0.22	1.68	0.24	1.64
Male	0.19	1.96	0.14	1.42
College Degree	-0.36	-4.47	-0.43	-5.00
Age index	-0.12	-0.47	-0.26	-1.07
Age index*Full day trip	0.16	0.72	0.19	0.81
Age index*Winter	0.65	3.09	0.62	2.84
Age index*June	-1.10	-4.65	-1.10	-4.79
Age index*Summer	-1.05	-4.18	-1.05	-4.14
Home in GOM	-1.07	-7.86	-0.89	-6.44
Home in GOM*Full day trip	0.63	4.96	0.64	4.92
Home in GOM*Winter	-0.03	-0.25	-0.06	-0.50
Home in GOM*June	-0.14	-1.12	-0.08	-0.68
Home in GOM*Summer	-0.14	-1.02	-0.04	-0.31
Satiation Parameter (α)	0.00[a]	1.01	0.00[b]	1.05

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Table 3 – *Continued from previous page*

	Model 1: Individual-specific, seasonal value of time (VOT_{ISS})		Model 2: Income-based value of time ($VOT_{1/3wage}$)	
	Estimate	*z*-stat	Estimate	*z*-stat
Translation Parameters (γ_t)				
Partial day trips				
Winter (γ_1)	0.34	9.21	0.34	8.70
June (γ_2)	0.20	5.64	0.20	5.54
Summer (γ_3)	0.15	4.73	0.14	4.57
Fall (γ_4)	0.38	8.70	0.38	8.18
Full day trips				
Winter (γ_5)	0.52	10.56	0.52	10.43
June (γ_6)	0.23	6.02	0.23	5.92
Summer (γ_7)	0.27	6.52	0.26	6.11
Fall (γ_8)	0.49	10.64	0.49	10.06
Scale Parameters				
Contingent behavior scale	0.85	44.84	0.86	42.42
Recall scale	0.91	47.59	0.90	46.09
N	2,439		2,439	
Log-likelihood (mean)	-18,762		-18,787	
In-sample RMSE	5.28		5.30	

Notes: This table reports estimates for the structural parameters of the Kuhn-Tucker model. Parameter estimates report the average point estimate from the bootstrapping procedure. The bootstrapping procedure is repeated 400 different times. *z*-stats are calculated using cluster bootstrap standard errors. GOM = Gulf of Mexico. RMSE = root mean squared error. *p < 0.1, **p < 0.05, and ***p < 0.01. Age index is calculated as the age of the respondent divided by the mean age. College Degree is a dummy variable if a respondent holds a bachelor or graduate degree.

[a] The value of 0.00 was the estimated value at convergence.

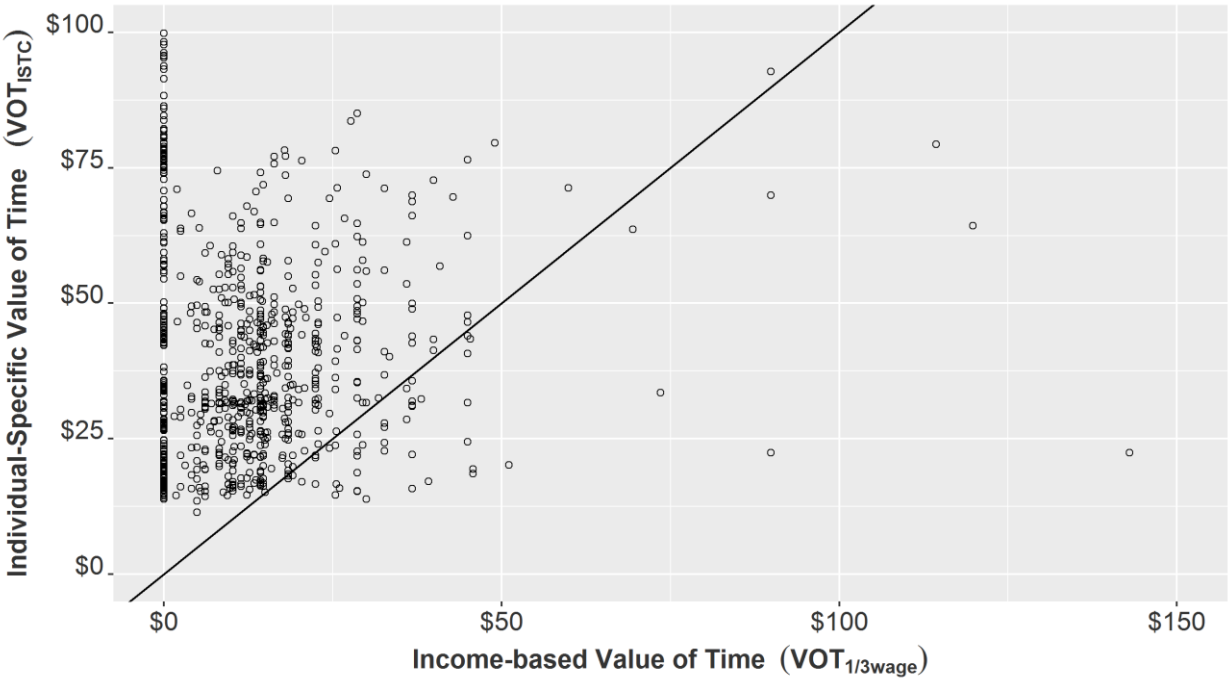
[b] The value of 0.00 was the estimated value at convergence.

Table 4: Welfare Estimates

Policy Scenario	Model 1: Individual-specific, seasonal value of time (VOT_{ISS})	Model 2: Income-based value of time ($VOT_{1/3wage}$)	Model 3: Individual-specific time-constant value of time (VOT_{ISTC})
	Mean welfare impacts ($/person/year)		
Policy 1: Trip fee increase all year ($25 partial/$50 full day)	-$128 (1.07)[a]	-$126 (0.19)	-$128 (1.02)
Policy 2: Summer fishing closure	-$501 (34)	-$298 (23)	-$422 (31)
Policy 3: Fall fishing closure	-$428 (16)	-$284 (12)	-$448 (17)

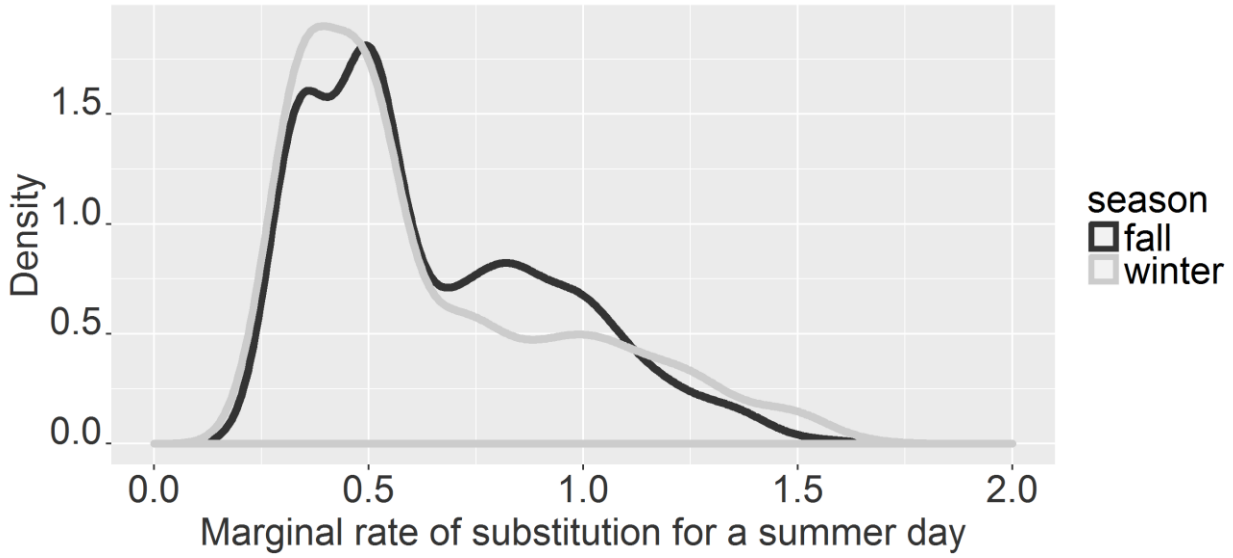
Notes: This table reports mean annual welfare impacts per individual of the three policies. Estimates are generated with 500 conditional error draws per individual. [a] Cluster bootstrap standard errors in parentheses.

Figure 1: Relationship between Value of Time Estimates per Hour using Individual-Specific and Income-Based Approaches



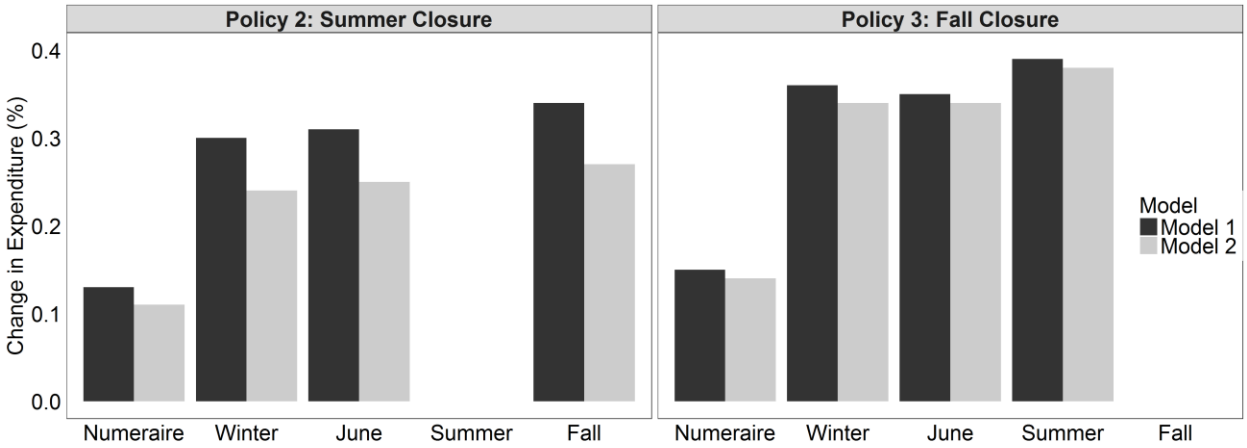
Notes: This figure plots the value of time measures from the individual-specific and income-based approaches to valuing time. Each dot represents a single individual. The 45 degree line indicates a perfect correspondence in estimates between the two approaches.

Figure 2: Distribution of Individual-Specific Estimates of Marginal Rates of Substitution (MRS) of Fall and Winter for Summer Leisure Days



Notes: This figure plots the distribution of individual estimates of the marginal rates of substitution of fall (black line) and winter days (grey line) for a summer day. Values less than one indicate summer leisure days are preferred to fall/winter days and values more than one indicate that fall/winter leisure days are preferred to summer days.

Figure 3: Behavioral Responses to Seasonal Closure Policies



Notes: This figure illustrates the average change in seasonal trip and numeraire expenditures as a result of a summer fishing closure (Policy 2) and a fall fishing closure (Policy 3) for Model 1 and Model 2.