Appalachian State University

Department of Economics Working Paper

Number 16-22| November 2016

Estimating Recreation Benefits through Joint Estimation of Revealed and Stated Preference Discrete Choice Data

John C. Whitehead
Appalachian State University

Daniel K. Lew
Alaska Fisheries Science Center

Department of Economics
Appalachian State University
Boone, NC 28608
Phone: (828) 262-2148
Fax: (828) 262-6105
www.business.appstate.edu/economics

Estimating Recreation Benefits through Joint Estimation of Revealed and Stated Preference Discrete Choice Data[1]

John C. Whitehead
Department of Economics
Appalachian State University
Boone, North Carolina

Daniel K. Lew
Alaska Fisheries Science Center
National Marine Fisheries Service
Seattle, Washington

November 3, 2016

[1] A previous version of this paper was presented at the Society for Benefit-Cost Analysis annual meeting in Washington, DC, March 2015 and seminars at Appalachian State University and Resources for the Future. The authors thank Trudy Cameron, Steve Kasperski, Kristy Wallmo, and seminar participants for numerous comments. Funding for this research was provided by the Alaska Fisheries Science Center, National Marine Fisheries Service. Opinions expressed are those of the authors and do not reflect those of NMFS, NOAA, or the U.S. Department of Commerce.

Estimating Recreation Benefits through Joint Estimation of Revealed and Stated Preference Discrete Choice Data

Abstract. We develop econometric models to jointly estimate revealed preference (RP) and stated preference (SP) models of recreational fishing behavior and preferences using survey data from the 2007 Alaska Saltwater Sportfishing Economic Survey. The RP data are from site choice survey questions, and the SP data are from a discrete choice experiment. Random utility models using only the RP data may be more likely to estimate the effect of cost on site selection well, but catch per day estimates may not reflect the benefits of the trip as perceived by anglers. The SP models may be more likely to estimate the effects of trip characteristics well, but less attention may be paid to the cost variable due to the hypothetical nature of the SP questions. The combination and joint estimation of RP and SP data seeks to exploit the contrasting strengths of both. We find that there are significant gains in econometric efficiency, and differences between RP and SP willingness to pay estimates are mitigated by joint estimation. We compare a number of models that have appeared in the environmental economics literature with the generalized multinomial logit model. The nested logit "trick" model fails to account for the panel nature of the data and is less preferred to the mixed logit error components model that accounts for panel data and scale differences. Naïve (1) scaled, (2) mixed logit, and (3) generalized multinomial logit models produced similar results to a generalized multinomial logit model that accounts for scale differences in RP and SP data. Willingness to pay estimates do not differ across these models but are greater than those in the mixed logit error components model.

Key words: discrete choice experiment, generalized multinomial logit model, hypothetical bias, revealed preference, stated preference, travel cost method

Introduction

The economic benefits of recreational activities can be estimated using revealed and stated preference data. The travel cost method (TCM) is a revealed preference approach that captures benefits that accrue to those who visit a recreation site and are assumed to prefer locations with better recreation opportunities and lower costs of access. Consider recreational fishing. Under the TCM, information on where and how often recreational fishing trips are taken, travel costs, and catch rates (or other measures of stock abundance) could be gathered using recreation surveys and used to determine recreational benefits. The discrete choice experiment (DCE) method is a stated preference approach that presents recreation alternatives, with varying costs and benefits, to respondents in a survey setting. Recreationists are asked which hypothetical recreation alternatives and/or locations they prefer. The revealed and stated preference decisions can be analyzed econometrically to determine the economic benefits of additional catch resulting from stock enhancement or other fisheries management actions.

Each of these approaches is a nonmarket valuation method. As such, the estimates of economic benefits must consider validity issues. Validity is the extent to which the measure of a theoretical construct (i.e., economic benefits) is accurately measured (Mitchell and Carson 1989; Freeman 2003). Validity can be enhanced by (1) using multiple valuation methods and (2) combining different types of data. Convergent validity is attained if two valuation approaches yield the same answer. For example, if TCM estimates are not statistically different than DCE estimates, then more confidence can be placed in both estimates. Combining revealed preference

(RP) and stated preference (SP) data allows another type of validity test by determining if individual decision makers are consistent in their decisions.

Another rationale for the use of multiple methods and data combination is the limitations of RP and SP data. Revealed preference data are constrained by history (i.e., past behavior), among other more technical limitations. Using historical data may make simulation of the effects of proposed fishery management policy (e.g., bag limits) more difficult due to the lack of variation in key variables. Stated preference data are constrained by the hypothetical nature of the survey task. Respondents may not fully understand the decision context or not take it as seriously as a real world decision. Combining RP and SP data may allow more accurate estimates of behavior beyond historical experience and ground hypothetical behavioral models in real world behavioral models. The combination and joint estimation of RP and SP data seeks to exploit the contrasting strengths of RP and SP data while minimizing their weaknesses (Whitehead et al. 2008; Whitehead, Haab, and Huang 2011).

In this paper we develop econometric models to jointly estimate RP and SP data models of recreational fishing behavior and preferences using survey data collected by the National Marine Fisheries Service (NMFS) (Lew, Lee, and Larson 2010). The RP data are site choice behavior and the SP data are from a discrete choice experiment. To our knowledge, this study is the first to use the generalized multinomial logit model to jointly model RP and SP choice data in the environmental economics literature, although the model has been applied to analyze SP alone (Hensher, Beck, and Rose 2011; Christie and Gibbons 2011; Scarpa, Thiene, and Hensher 2012; Kragt 2013; Lew and Wallmo 2017). We compare results from this model to econometric models used in the few previous joint estimation efforts in this literature. The policy context is the Halibut Catch Sharing Plan adopted by the North Pacific Fishery Management Council (NPFMC) and implemented by NMFS. Under this plan, the NPFMC annually reviews charter sector-specific regulations, and makes recommendations about measures to manage recreational harvest of Pacific halibut for the upcoming year. The paper's goal is to explore how combining RP and SP data in different discrete choice models may lead to better estimates of the demand and value of saltwater recreational fishing in Alaska, with a primary emphasis on Pacific halibut and its primary economic substitutes and complements, Pacific salmon.

Joint Estimation Literature

The RP and SP data have been separately analyzed by Lew and Larson (2011, 2012, 2014) and Larson and Lew (2013). The RP models use travel and time costs measured by distance to various fishing sites and income data reported in the survey. The trip benefits are measured by catch per day estimated from creel surveys and from estimates provided by the anglers themselves. The SP models use a total trip cost measure that does not make explicit travel distance or time cost. Expected catch and keep per trip and other attributes are included as attributes in the choice experiment. In this context, the strengths of the RP data are also the weaknesses of the SP data, and vice versa, so that the RP and SP data should be considered complementary.

Data combination can be used to mitigate problems in both RP and SP data. In short, the RP models may be more likely to provide an unbiased estimate of the effect of cost on site selection but catch estimates may not reflect the benefits of the trip as perceived by anglers.[2] Site/species-specific revealed preference catch estimates do not vary across anglers and, therefore, may be highly correlated. Multicollinearity may hinder estimation of unbiased catch coefficients. Estimation of individual/site specific catch rates is feasible but the data often does not support estimation (Haab et al. 2012). Also, the revealed preference data are limited to analyzing behavior in response to a limited range of catch per day variation across sites. The discrete choice experiment is designed to collect data on hypothetical behavior with individual variation in catch rates, which can span beyond observed levels.

The SP models are more likely to estimate unbiased coefficients for trip attributes (including catch) but the cost coefficient may suffer from attribute non-attendance (which would manifest as hypothetical bias). If respondents pay less than full attention to the cost variable it will be biased downward (in absolute value) leading to upwardly biased willingness to pay estimates (Campbell, Hensher, and Scarpa 2012; Colombo, Christie, and Hanley 2013)[3]. There is evidence of hypothetical bias of choice experiment data in the transportation (e.g., Fifer, Rose, and Greaves 2014) and agricultural (e.g., Lusk and Schroeder 2004) economics literatures. Metcalfe et al. (2012) find that total willingness to pay is higher with choice experiment data relative to comparable contingent valuation data. They scale the willingness to pay estimates from choice experiment data down by the choice experiment-contingent valuation ratio of total

---

[2] The RP cost will be unbiased under the assumption that the travel cost variable is not measured with error (Randall 1994).

[3] Attribute non-attendance is not limited to cost (e.g., Colombo, Christie, and Hanley 2013).

willingness to pay. Various methods have been used to mitigate hypothetical bias in choice experiments (Lusk 2003; Ready, Champ, and Lawton 2010; Araña and León 2013; de-Magistris, Gracia and Nayga 2013; de-Magistris and Pascucci 2014) but recognition of the problem and a willingness to address the issue in the environmental economics DCE literature is not widespread (Hoyos 2010).[4]

Combining RP and SP data grounds hypothetical choices with real choice behavior and may reduce hypothetical bias (Hoyos 2010, Hensher 2010). While there have been a number of RP and SP joint estimation applications in other literatures and the DCE literature in environmental economics has exploded, we know of only four applications in environmental economics that combine RP and SP DCE data. Adamowicz, Louviere, and Williams (1994) present the first application of RP and SP joint estimation using choice experiments in the environmental economics literature. They find that the RP data are limited due to collinearity and the SP data are prone to hypothetical bias. Adamowicz, et al. (1997) present an application to moose hunting with a focus on a comparison of RP and SP models with objective or subjective characteristics of the choices. They conclude that the jointly estimated RP and SP model with subjective characteristics outperforms the other models, suggesting that RP models are limited by the lack of subjective measurement of choice attributes. Both of these studies combine data using the nested logit "trick" (Hensher and Bradley 1993). Using the Adamowicz et al. data, von Haefen and Phaneuf (2008) extend the model by including observed and unobserved preference heterogeneity. They reject the hypothesis of consistency between the RP and SP data (i.e.,

[4] See Krucien, Gafni, and Pelletier-Fleury (2015), Lancsar and Swait (2014) and Fifer, Simon, Rose, and Greaves (2014) for discussion in the health and transportation literatures.

equality of coefficients across data sources) and illustrate how sensitivity analysis can be used to account for the inconsistency. Abildtrup, Olsen, and Stenger (2015) estimate forest recreation choices with a mixed logit error components model (Hensher, Rose, and Greene 2008). They find significant hypothetical bias in the choice experiment data.

In the next section we describe the models available for RP and SP data combination. These include the nested logit "trick," the mixed logit error components model, and the generalized multinomial logit model. Then we describe the data. Since the survey was not specifically designed for joint estimation, we manipulate the RP and SP data in order to create a parallel data set suitable for an illustrative example. Then we present the results comparing a range of models. Finally, we offer some conclusions and directions for future research.

Models

Both the RP and SP data we analyze represent discrete choices made by individuals between multiple fishing (and non-fishing) alternatives. Random utility theory is the basis for recreational fishing models involving joint estimation of these discrete RP and SP choices,

$$U_{ij} = \boldsymbol{\beta}'\boldsymbol{x}_{ij} + \varepsilon_{ij}/\sigma, \tag{1}$$

where U_{ij} is the utility angler i receives from fishing alternative j, $i = 1, \ldots, I$, $j = 1, \ldots, J$, $\boldsymbol{\beta}'\boldsymbol{x}_{ij}$ is the systematic portion of utility, $\boldsymbol{\beta}$ is a vector of parameters, $\boldsymbol{x}_{ij}$ is a vector of variables specific to the choice (e.g., travel cost, catch), ε is the random error and σ is the standard deviation of the error term, i.e., the scale parameter. Multiplying through by the scale parameter angler utility becomes

(2) $$U'_{ij} = \sigma\boldsymbol{\beta}'\boldsymbol{x}_{ij} + \varepsilon_{ij},$$

where the scale parameter is normalized to one in order to identify the coefficients when a single dataset is used. Given the unobserved elements of utility, we consider the probability of individual *i* choosing alternative *j* is

(3) $$\pi_{ij} = Pr\left(\sigma\boldsymbol{\beta}'\boldsymbol{x}_{ij} + \varepsilon_{ij} > \sigma\boldsymbol{\beta}'\boldsymbol{x}_{ik} + \varepsilon_{ik}; \forall k \in J\right).$$

The multinomial logit (MNL) model assumes the error terms in (2) are independent and identically distributed (iid) extreme value (also known as Gumbel) variates; as a consequence, the probability of a choice alternative takes the form:

(4) $$\pi_{ij} = \frac{exp\left(\sigma\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}}\right)}{\sum_{j=1}^{J} exp\left(\sigma\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}}\right)}.$$

In the MNL model the model parameters describing site choice are assumed to be constant across individuals, indicating homogeneous response to site characteristics.

A number of discrete choice models have been developed to combine discrete choice RP and SP data. A naïve approach simply stacks the data and employs the MNL model. When RP or SP data are estimated separately the scale parameter in the multinomial logit is arbitrarily set equal to one. This is naïve because when RP and SP data are stacked and estimated jointly, it is common for the error terms that result from the different data to have unequal variance leading to unequal scale parameters (Swait and Louviere 1993). It is typical, but not universal, for the SP data to have a higher variance due, perhaps, to the unfamiliarity of the choice task. The difference in the scale parameter will cause the MNL coefficients to differ across RP and SP data sets. In this case the RP coefficient estimates will be proportionately larger than the SP coefficient estimates since the variance of the error term is an inverse function of the scale factor (Swait and Louiviere 1993).

The relative scale factor in a stacked data set can be estimated as described by Hensher and Bradley (1993), Hensher, Rose and Greene (2005) and Whitehead (2011). The so-called nested logit "trick" involves creating a choice situation for each RP (SP) observation that counterfactually also includes the SP (RP) alternatives. The model is then estimated as a nested logit with the inclusive value for the RP branch set equal to one. The SP alternatives are estimated in individual branches but with the inclusive value for each branch constrained to be equal. The variance of the RP nest is constrained to equal one while the variance of the SP alternatives is allowed to diverge from one. When the scale parameter for the RP data is set equal to one the nested logit model will estimate the relative scale factor for the SP data as the inclusive value for the SP data. The SP data are then appropriately scaled and the coefficients can be estimated jointly without one dataset having a larger influence than the other.

One problem with the nested logit "trick" is the assumption that the stacked RP and SP observations from each angler are independent (Hensher, Rose, and Greene 2008). In contrast, mixed logit (MXL) discrete choice models capture the panel nature of the data, allow correlation across choices for each angler, are capable of estimating scale parameters and allow for random parameters in the utility specification (Train 2003):

(5) $$U_{ij} = (\boldsymbol{\beta} + \boldsymbol{\eta}_i)'\boldsymbol{x}_{ij} + \varepsilon_{ij},$$

where $\boldsymbol{\beta}$ is the mean parameter estimate, $\boldsymbol{\eta_i}$ is the individual specific deviation from the mean parameter estimate, and the error terms are Gumbel distributed. Brownstone, Bunch, and Train (2000) and Greene and Hensher (2007) develop a mixed logit error components model where scale is estimated as the standard deviation of alternative specific SP random coefficients where the mean effect is constrained to zero. The scale parameters are estimated by including alternative specific constants for the SP alternatives with zero mean and free variance. Hensher (2008) and Börjesson (2008) provide examples of its estimation in the transportation context. Abildtrup, Olsen and Stenger (2015) use the model in the recreation context.

While the random parameters in the MXL model introduce preference heterogeneity in the model, a recent alternative has been proposed that accounts for scale heterogeneity that may result from some individuals having a systematically larger (or smaller) scale (error variance). This alternative model is the scaled MNL (SMNL) model that accounts for scale differences by allowing individuals to have different scale parameters (Fiebig et al. 2010). In effect, the model estimates parameters that describe the distribution of scale (Hensher 2012):

(6) $$U_{ij} = \sigma_i \boldsymbol{\beta}'\boldsymbol{x}_{ij} + \varepsilon_{ij}.$$

Both preference and scale heterogeneity are captured in a third model, the generalized multinomial logit (GMXL) model (Fiebig et al. 2010; Keane and Wasi 2013):[5]

[5] The ability of the GMXL to separately estimate individual-level scale and preference heterogeneity has been challenged recently by Hess and Rose (2012), who argue that the utility specifications in GMXL models simply allow for more flexible distributions of the preference parameters.

(7) $$U_{ij} = [\sigma_i \boldsymbol{\beta} + \gamma \boldsymbol{\eta_i} + (1-\gamma)\sigma_i \boldsymbol{\eta_i}]' \boldsymbol{x}_{ij} + \varepsilon_{ij}$$

where γ is a weighting variable that allows for scaling of the unobserved heterogeneity in the parameters. When $\gamma = 1$ there is no scaling of the preference heterogeneity. Fiebig et al. (2010) called this model GMXL-I:

(8) $$U_{ij} = [\sigma_i \boldsymbol{\beta} + \boldsymbol{\eta}_i]' \boldsymbol{x}_{ij} + \varepsilon_{ij},$$

when $\gamma = 0$ the preference heterogeneity is scaled. Fiebig et al. (2010) called this model GMXL-II:

(9) $$U_{ij} = [\sigma_i \boldsymbol{\beta} + \sigma_i \boldsymbol{\eta_i}]' \boldsymbol{x}_{ij} + \varepsilon_{ij}.$$

The scale parameter in the GMXL models takes the form

(10) $$\sigma_i = exp(-\tau^2/2 + \theta SP + \tau w_i),$$

where τ is the coefficient on the unobserved scale heterogeneity, w_i, which is assumed to follow a standard normal distribution, and *SP* is equal to one for the stated preference data source and zero otherwise (Hensher 2012).

Individual angler preferences differ randomly according to a specified distribution, *f*(***ß***), so that the unconditional site choice probability takes the form:

(11) $$\pi_{ij} = \int \frac{exp(\boldsymbol{\varphi}' x_{ij})}{\sum_{j=1}^{J} exp(\boldsymbol{\varphi}' x_{ij})} f(\boldsymbol{\varphi}) d\boldsymbol{\varphi}.$$

where $\boldsymbol{\varphi} = \sigma_i\boldsymbol{\beta} + \gamma\boldsymbol{\eta}_i + (1-\gamma)\sigma_i\boldsymbol{\eta}_i$. The probability is evaluated over the distribution of both the random preference parameters ($\boldsymbol{\eta}_i$) and the individual scale heterogeneity (w_i) and does not have a closed form solution. Therefore, estimation of the parameters requires simulation of the integral. See Greene and Hensher (2010) for details.

Data

A 2007 survey of Alaska saltwater anglers collected information on saltwater fishing participation, effort, and preferences of resident and non-resident anglers during the 2006 fishing season. The survey was administered to three groups of anglers for which separate survey instruments were developed: non-residents, residents of Southeast Alaska, and all other Alaska residents.[6] In this study we focus on the Southeast Alaska resident angler data which were analyzed in Larson and Lew (2013) and Lew and Larson (2014). Using a repeated mixed logit RP model the authors show how multiple sources of catch data, both from exogenous creel surveys and from self-reported survey data by the sample itself, could be used in the same model and weighted to provide improved value estimates (Larson and Lew 2013). The Southeast Alaska SP data were analyzed in Lew and Larson (2014) which focused on the relationship between catch and keep and catch and release rates.

In this study, we focus on a sample of Southeast Alaska resident anglers who took a private boat trip to a Southeast Alaska fishing site and also answered each of four stated

[6] Lew, Lee, and Larson (2010) describe the development, content, and structure of the three survey versions, their implementation, and a summary of the data.

preference questions (n = 204). There is a preponderance of nonusers in the full sample and the no RP trip option makes combining data less informative (e.g., the no trip option dummy variable is strongly positive in the RP data). Only considering users in this exercise puts an emphasis on the gains from combining data from a sample where the opt-out option can only be identified in the SP data, such as for intercept samples (Whitehead 2011). As a result, this type of data combination will be most informative to other recreation demand choice experiment models that can be combined with surveys of on-site users. In Table 1, we summarize the data. Sixty-seven percent of the sample is male and the average age is 47. The average number of years of fishing experience is 23. Average income is $80,000 and the average household size is 2.3 persons. The average number of fishing trips to Southeast Alaska sites is 12 with a range of 1 to 50.

In order to combine data, it is often recommended to have the same number of observations so that neither data source dominates in estimation. There are $k = 4$ SP observations (i.e., trip preferences) for each of the 204 survey respondents and 2245 RP trips over $j = 10$ sites in the data (Table 1). We use the "typical" trip to define site choice over four choice occasions for the RP site choice data. We define the typical trip as equal to one if the site has the maximum number of trips for the respondent: $ttrip_j = 1$ for $j = \max(trips_j)$ and 0 otherwise. There are four ties in the data. In this case the typical trip site was chosen randomly by the computer.

The distribution of typical trips across the $j = 10$ sites is very similar to the distribution of total trips (Table 2).[7] The percentage of total trips ranges from 0.4% at Kake to 41% at Juneau (Figure 2). The typical trips range from 1% at Kake and Yakutat to 43% at Juneau. In Table 2, we also present the travel cost and catch and keep rates for each site. The mean travel costs range from $39 at Juneau to $192 at Yakutat. The catch and keep rates are estimated from the 2007 survey for halibut, king (chinook) and silver (coho) salmon. The mean halibut catch ranges from 0.07 per trip at Haines-Skagway to 0.69 per trip at Glacier Bay.[8] The mean king salmon catch ranges from 0.05 per trip at Glacier Bay to 0.42 per trip at Sitka. The mean silver salmon catch ranges from 0.01 per trip at Yakutat to 0.73 per trip at Prince of Wales. The catch rates vary across sites but not within sites (i.e., the standard deviation is zero at each site) which is a limitation of the RP recreational fishing data.

The SP site choice data are adapted from a contingent ranking exercise where respondents are asked for their most preferred and least preferred of three alternatives in each choice occasion (recall there are four for the SP data). The first two alternatives (A, B) are fishing trips that vary over fishing mode, fishing days, target species, daily bag limit, actual catch and size, and cost per trip. Catch levels are truncated where the actual catch exceeds the daily bag limit. Alternative C is the no trip alternative. We assume that respondents would choose the fishing site that they rate as their most preferred. We delete cases where choices are ambiguous

---

[7] Alternatively, we could randomly choose each of the $k = 4$ sites for respondents who take more than one trip.

[8] These rates were calculated over trips targeting any species, not just those targeting halibut or salmon.

in the raw data (e.g., respondent chooses same alternative as best and worst). Anglers choose almost equally across alternatives A and B (Table 3). About 10% of the anglers prefer no trip across the four choice occasions. The mean travel cost ranges from $71 to $115. Mean halibut catch per trip ranges from 0.50 to 1.15. Mean king salmon catch per trip ranges from 0.58 to 1.18. Mean silver salmon catch per trip ranges from 0.21 to 1.87.

Results

We estimate four sets of models. We first estimate separate RP and SP models to illustrate the limitations of both types of data. We then combine the data in the nested logit "trick" structure and estimate the nested logit and mixed logit error component models. Next, we stack the data without the contrived structure of the previous models and estimate the naïve scaled multinomial logit and mixed logit models. Finally, we estimate two alternative generalized multinomial logit models. We specify simple models that include cost, catch rates and a no trip alternative specific constant interacted with income. The preference heterogeneity in each mixed logit model is specified as normally distributed for the catch rate variables. Each of the standard deviations reach into the negative realm but a similar pattern of results is found for the triangular distribution which constrains the catch rate parameter distribution to the positive realm.[9]

The separately estimated RP site selection and SP choice experiment models are

[9] These results and others mentioned in this section are available upon request.

presented in Table 4.[10] The travel cost coefficient is negative and highly statistically significant in the multinomial logit RP model. Each of the catch coefficients is positive but only the king salmon coefficient is statistically significant in the RP model. The coefficient on the key variable of policy interest, halibut catch, is not statistically significant. This is likely due to the limited variation in catch rates across sites and the relatively low halibut catch at the most visited site. In the mixed logit SP model the coefficient on the travel cost is negative but only marginally significant. The travel cost coefficient is an order of magnitude lower than that in the RP model (in absolute value). The coefficients for halibut and king salmon catch are positive and statistically significant. The king salmon coefficient is an order of magnitude larger than that in the SP model. The coefficient on silver salmon is not statistically significant. The coefficient on the no trip option interacted with income is negative. This indicates that anglers with higher incomes are more likely to choose to take either trip A or trip B.

Next, the data are stacked with the nested logit "trick" data structure and jointly estimated (Table 5). Several gains from joint estimation are observed. In contrast to the independently estimated models, all of the coefficients are estimated more efficiently due to the simple fact that there are more observations. The RP data influences the parameter estimates more than the SP data in the nested logit model. Each of the coefficient estimates are of similar magnitude compared to the RP data model. The scale factor is very large in the nested logit model. This suggests that there is extreme heteroskedasticity in SP data when compared to RP data after

---

[10] All of these models are estimated with NLOGIT software (Greene 2012; Chang and Lusk 2011).

stacking the uniform RP choices, which may artificially introduce less randomness in the RP data. In contrast, the SP data dominates in the error components model with catch rate coefficients similar in magnitude to the independently estimated SP model. The travel cost coefficient is increased in absolute value so that it is only about 50% lower as the independently estimated RP model travel cost coefficient. Only the king salmon standard deviation is statistically different from zero. The alternative specific scale factors are statistically significant for alternatives A and C (no trip).

We next apply the scale MNL and mixed logit models to the combined RP and SP data (Table 6). These models are "naïve" in that they do not consider differences in scale across data sources. Each of the coefficient estimates is statistically different from zero. The travel cost coefficients are similar in magnitude to that in the RP data model. The coefficient on τ in the scale parameter is statistically different from zero indicating some support for the scaled model.[11] Results for the mixed logit model are similar. Each of the standard deviations on the catch rate coefficients is statistically different from zero. We find that the mixed logit is statistically superior with lower AIC and higher pseudo-R^2 values.

The generalized multinomial logit model is estimated with the γ weighting parameter set to one (i.e., GMXL-I). When we restrict the γ parameter to zero and estimate GMXL-II the coefficient on θ, the SP contribution to the τ scale, changes sign and increases by an order of magnitude (in absolute value). When the model is estimated with γ unconstrained, γ is greater

[11] We also attempted to estimate the θ coefficient by including the SP dummy variable in the estimation of τ. However, this model did not converge successfully.

than one. While γ can be treated as a parameter to be estimated and can range beyond 0 and 1 (Keane and Wasi 2013), we restrict our attention to GMXL-I.

All of the generalized multinomial logit coefficient estimates are statistically different from zero (Table 7). The first model is naïve in that it does not account for differences in scale across data sources. It is a combination of the scale and mixed logit models in Table 6 and the results are very similar. It is statistically preferred to both models in Table 6 with lower AIC and higher pseudo-R^2 values. In order to estimate the generalized multinomial logit model while controlling for SP scale differences (GMXL-I-SP), we fix τ at 0.5 as in Hensher (2012).[12] The magnitudes of the coefficient estimates are similar to the naïve model. Standard deviations of the catch coefficients are slightly higher. The coefficient on the SP contribution to scale, θ, is positive and statistically different from zero indicating a larger variance in the SP data relative to the RP data. The AIC and pseudo-R^2 values indicate a slight preference for the naïve model with individual scale parameters.

Willingness to Pay

The independently estimated RP and SP models and jointly estimated RP and SP models can be used to estimate a willingness-to-pay (WTP) for changes in the non-cost attributes. Haab and McConnell (2002) show that the marginal WTP for a change in catch for each fishing trip is

[12]The model fails to converge when τ is unconstrained while including the SP dummy variable. Similar results, other than a larger θ parameter, are found with τ fixed at 0.25. When τ is fixed at 0.75 the model fails to estimate satisfactorily.

the ratio of the catch ($\boldsymbol{\beta_q}$) and travel cost (β_c) coefficients, $\frac{\boldsymbol{\beta_q}}{\beta_c}$, where q denotes the catch and c denotes the cost. Since the coefficient on travel cost is in the denominator of the willingness to pay function, it plays a large role in value determination. Hypothetical bias in SP cost coefficients will lead to upward bias in WTP for catch.

The pattern of WTP estimates is similar across models with king salmon valued highest in each (Table 8). Notably, WTP for halibut or silver salmon is not statistically significant in the RP model.[13] The WTP estimates in the SP models are significantly higher than in the RP models given the small travel cost coefficient. But, SP WTP estimates are also not significantly different from zero given the statistical insignificance of the SP travel cost coefficient. The WTP estimates from the more flexibly estimated scaled and mixed logit SP models are lower for king salmon relative to the RP estimate. The jointly estimated halibut WTP estimates fall in between the RP and SP estimates and are statistically significant. The silver salmon WTP estimates in the jointly estimated models are all similar to the RP model WTP estimates, but statistically different from zero. The silver salmon WTP is lower with statistically significant differences than the halibut and king salmon *WTP* estimates in all of the scaled and mixed logit models. The WTP estimates for halibut and king salmon are not statistically different except for those from the generalized multinomial logit with SP scale differences model which have non-overlapping

[13] This is also true in the model that uses all 2245 trips instead of the typical trip.

confidence intervals.

Discussion and Conclusion

This paper is the first attempt to combine site choice RP and discrete choice experiment SP data with the generalized multinomial logit model in the environmental economics literature. Our results illustrate the benefits of joint estimation even with data that were collected without joint estimation in the study design. This study finds that there are two significant gains to jointly estimating RP recreation trip and SP choice experiment data–econometric efficiency is increased and bias in RP and SP willingness-to-pay estimates are mitigated by joint estimation. The only model where the SP scale parameter made a significant difference was in the nested logit "trick" model. This model fails to account for the panel nature of the data and is less preferred statistically to scale and mixed logit models that account for panel data and scale differences. With these data we found scale differences across data sources in several models. The generalized multinomial logit models outperformed the others statistically, but there is little difference in willingness to pay estimates.

These results should not be directly compared to the earlier Lew and Larson papers since we used a subset of the RP data and our interpretation of the data differs. The Alaska sport fishing survey was not designed to collect data for RP and SP joint estimation. In order to appropriately combine the data we made a number of data decisions that could lead to differences in separate RP and SP analyses. Nevertheless, the data handling decisions made here are not invalid; that is, the separate RP and SP analyses in this study are different, but valid, approaches to obtaining willingness to pay values.

While these results are instructive they should only be considered as illustrative. In our models we have simplified the data to (1) focus on variables that are contained in both the RP and SP data (travel cost and catch) and (2) assess the simplest RP choice scenarios. Considering (1), it is not necessary for the RP and SP coefficients vectors to contain the same elements. In fact, it is typical for RP data sets to have some variables that do not vary or are unobserved across individuals. In this case, the SP data could be used to identify the effect of the variable on the choices. Also, SP choice experiments may be difficult to design with some attributes that are relatively easy to estimate with RP data. Future research should strive to design, collect and more consistently measure attributes so as to fully exploit the gains from combining RP and SP data.

Still, our results raise questions about much of the SP choice experiment literature in environmental economics. Even with the attention accorded to the Adamowicz, Louviere, and Williams (1994) seminal contribution, the choice experiment literature has proceeded with little to no attention paid to its similarities to RP data. This is in stark contrast to the contingent valuation and contingent behavior literatures which have spent considerable time comparing and jointly estimating RP and SP data (Carson et al. 1996; Whitehead, Haab, and Huang 2011).

The lack of attention to the issue of hypothetical bias may be due to the fact that many SP choice experiments are not designed as behavioral surveys. With the Southeast Alaska fishing data we assumed that a ranking of the "best" trip would be a chosen trip. Many other choice experiments are designed to elicit non-behavioral preferences and elicit nonuse values for which there is no behavioral trace. Our results suggest that choice experiment survey design should pay more attention to their behavioral counterparts and attempt to exploit the gains from joint estimation.

References

Abildtrup, Jens, Søren Bøye Olsen, and Anne Stenger. 2015. Combining RP and SP data while accounting for large choice sets and travel mode–an application to forest recreation. *Journal of Environmental Economics and Policy* 4(2): 177-201.

Adamowicz, Wiktor, Jordan Louviere, and Michael Williams. 1994. Combining revealed and stated preference methods for valuing environmental amenities, *Journal of Environmental Economics and Management* 26: 271-292.

Adamowicz, Wiktor, Joffre Swait, Peter Boxall, Jordan Louviere, and Michael Williams. 1997. Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation, *Journal of Environmental Economics and Management* 32: 65-84.

Araña, Jorge E., and Carmelo J. León. 2013. Dynamic hypothetical bias in discrete choice experiments: Evidence from measuring the impact of corporate social responsibility on consumers demand. *Ecological Economics* 87: 53-61.

Börjesson, Maria. 2008. Joint RP–SP data in a mixed logit analysis of trip timing decisions. *Transportation Research Part E: Logistics and Transportation Review* 44(6): 1025-1038.

Brownstone, David, David S. Bunch, and Kenneth Train. 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transportation Research Part B: Methodological* 34(5)): 315-338.

Campbell, Danny, David A. Hensher, and Riccardo Scarpa. 2012. Cost thresholds, cut-offs and sensitivities in stated choice analysis: identification and implications. *Resource and Energy Economics* 34(3): 396-411.

Carson, Richard T., Nicholas E. Flores, Kerry M. Martin, and Jennifer L. Wright. 1996. Contingent valuation and revealed preference methodologies: comparing the estimates for quasi-public goods. *Land Economics* 72(1): 80-99.

Chang, Jae Bong, and Jayson L. Lusk. 2011. Mixed logit models: accuracy and software choice. *Journal of Applied Econometrics* 26(1): 167-172.

Christie, Mike, and James Gibbons. 2011. The effect of individual 'ability to choose' (scale heterogeneity) on the valuation of environmental goods. *Ecological Economics* 70: 2250-2257.

Colombo, Sergio, Michael Christie, and Nick Hanley. 2013. What are the consequences of ignoring attributes in choice experiments? Implications for ecosystem service valuation. *Ecological Economics* 96: 25-35.

de-Magistris, Tiziana, Azucena Gracia, and Rodolfo M. Nayga. 2013. On the use of honesty priming tasks to mitigate hypothetical bias in choice experiments. *American Journal of Agricultural Economics* 95(5): 1136-1154.

de-Magistris, Tiziana, and Stefano Pascucci. 2014. The effect of the solemn oath script in hypothetical choice experiment survey: A pilot study. *Economics Letters* 123(2): 252-255.

Fiebig, Denzil G., Michael P. Keane, Jordan Louviere, and Nada Wasi. 2010. The generalized multinomial logit model: accounting for scale and coefficient heterogeneity. *Marketing Science* 29(3): 393-421.

Fifer, Simon, John Rose, and Stephen Greaves. 2014. Hypothetical bias in Stated Choice Experiments: Is it a problem? And if so, how do we deal with it? *Transportation Research Part A: Policy and Practice* 61: 164-177.

Freeman, A. Myrick. 2003. *The Measurement of Environmental and Resource Values: Theory and Methods*, 2nd edition. Washington, D.C.: Resources for the Future.

Greene, William H. 2012. *NLOGIT 5.0.*, Plainview, New York: Econometric Software.

Greene, William H., and David A. Hensher. 2007. Heteroscedastic control for random coefficients and error components in mixed logit. *Transportation Research Part E: Logistics and Transportation Review* 43(5): 610-623.

Greene, William H., and David A. Hensher. 2010. Does scale heterogeneity across individuals matter? An empirical assessment of alternative logit models. Transportation 37(3): 413-428.

Haab, Timothy, Robert Hicks, Kurt Schnier, and John C. Whitehead. 2012. Angler heterogeneity and the species-specific demand for marine recreational fishing. *Marine Resource Economics* 27(3): 229-251.

Haab, Timothy, and Kenneth E. McConnell. 2002. *Valuing Environmental and Natural Resources*: *The Econometrics of Non-Market Valuation*. Cheltenham, U.K.: Edward Elgar Publishing.

Hensher, David A. 2008. Empirical approaches to combining revealed and stated preference data: some recent developments with reference to urban mode choice. *Research in Transportation Economics* 23(1): 23-29.

Hensher, David A. 2010. Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B: Methodological* 44(6): 735-752.

Hensher, David A. 2012. Accounting for scale heterogeneity within and between pooled data sources. *Transportation Research Part A: Policy and Practice* 46(3): 480-486.

Hensher, David A., Matthew J. Beck, and John M. Rose. 2011. Accounting for preference and scale heterogeneity in establishing whether it matters who is interviewed to reveal household automobile purchase preferences. *Environmental and Resource Economics* 49: 1-22.

Hensher, David A., and Mark Bradley. 1993. Using stated response choice data to enrich revealed preference discrete choice models. *Marketing Letters* 4(2): 139-151.

Hensher, David A., John M. Rose, and William H. Greene (2005) *Applied Choice Analysis: A Primer*, Cambridge, U.K.: Cambridge University Press.

Hensher, David A., John M. Rose, and William H. Greene. 2008. Combining RP and SP data: biases in using the nested logit 'trick'–contrasts with flexible mixed logit incorporating panel and scale effects. *Journal of Transport Geography* 16(2): 126-133.

Hess, Stephane, and John M. Rose. 2012. Can Scale and Coefficient Heterogeneity Be Separated in Random Coefficients Models? *Transportation* 39(6): 1225-1239.

Hoyos, David. 2010. The state of the art of environmental valuation with discrete choice experiments. *Ecological Economics* 69(8): 1595-1603.

Keane, Michael, and Nada Wasi. 2013. Comparing Alternative Models of Heterogeneity in Consumer Choice Behavior. *Journal of Applied Econometrics* 28: 1018-1045.

Kragt, Marit E. 2013. The effects of changing cost vectors on choices and scale heterogeneity. *Environmental and Resource Economics* 54: 201-221.

Krucien, Nicolas, Amiram Gafni, and Nathalie Pelletier-Fleury. 2015. Empirical testing of the external validity of a discrete choice experiment to determine preferred treatment option: The case of sleep apnea. *Health Economics* 24(8): 951-965.

Lancsar, Emily, and Joffre Swait. 2014. Reconceptualising the External Validity of Discrete Choice Experiments. *PharmacoEconomics* 32(10): 951-965.

Larson, Douglas M., and Daniel K. Lew. 2013. How Do Harvest Rates Affect Angler Trip Patterns? *Marine Resource Economics* 28(2): 155-173.

Lew, Daniel K., Jean Lee, and Douglas M. Larson. 2010. Saltwater sportfishing in Alaska: A summary and description of the Alaska saltwater sportfishing economic survey, 2007. U.S. Department of Commerce, NOAA Technical Memorandum NMFS-AFSC-214, 229 pages.

Lew, Daniel K., and Douglas M. Larson. 2011. A Repeated Mixed Logit Approach to Valuing a Local Sport Fishery: The Case of Southeast Alaska Salmon. *Land Economics* 87(4): 712-729.

Lew, Daniel K., and Douglas M. Larson. 2012. Economic Values for Saltwater Sport Fishing in Alaska: A Stated Preference Analysis. *North American Journal of Fisheries Management* 32(4): 745-759.

Lew, Daniel K., and Douglas M. Larson. 2014. Is a fish in hand worth two in the sea? Evidence from a stated preference study. *Fisheries Research* 157: 124-135.

Lew, Daniel K., and Kristy Wallmo. 2017. Temporal stability of stated preferences for endangered species protection from choice experiments. *Ecological Economics* 131: 87-97.

Lusk, Jayson L. 2003. Effects of cheap talk on consumer willingness-to-pay for golden rice. *American Journal of Agricultural Economics* 85(4): 840-856.

Lusk, Jayson L., and Ted C. Schroeder. 2004. Are choice experiments incentive compatible? A test with quality differentiated beef steaks. *American Journal of Agricultural Economics* 86(2): 467-482.

Metcalfe, Paul J.,William Baker, Kevin Andrews, Giles Atkinson, Ian J. Bateman, Sarah Butler, Richard T. Carson, Jo East, Yves Gueron, Rob Sheldon, and Kenneth Train. 2012. An assessment of the nonmarket benefits of the Water Framework Directive for households in England and Wales. *Water Resources Research* 48: W03526.

Mitchell, Robert C., and Richard T. Carson. 1989. *Using Surveys to Value Public Goods: The Contingent Valuation Method.* Washington, D.C.: Resources for the Future.

Randall, Alan. 1994. A difficulty with the travel cost method. *Land Economics* 70(1): 88-96.

Ready, Richard C., Patricia A. Champ, and Jennifer L. Lawton. 2010. Using respondent uncertainty to mitigate hypothetical bias in a stated choice experiment. *Land Economics* 86(2): 363-381.

Scarpa, Ricarrdo., Mara Thiene, and David A. Hensher. 2012. Preferences for tap water attributes within couples: An exploration of alternative mixed logit parameterizations. *Water Resources Research* 48: W01520.

Swait, Joffre, and Jordan Louviere. 1993. The role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of Marketing Research* 30(3): 305-314.

Train, Kenneth E. 2003. *Discrete Choice Methods with Simulation*. Cambridge, UK: Cambridge, U.K.: Cambridge University Press

von Haefen, Roger F., and Daniel J. Phaneuf. 2008. Identifying demand parameters in the presence of unobservables: a combined revealed and stated preference approach. *Journal of Environmental Economics and Management* 56:19-32.

Whitehead, John. 2011. Multiple choice discrete data joint estimation. In *Preference Data for Environmental Valuation: Combining Revealed and Stated Approaches*, eds. Whitehead, John, Tim Haab, and Ju-Chin Huang. New York: Routledge.

Whitehead, John, Tim Haab, and Ju-Chin Huang, eds. 2011. *Preference Data for Environmental Valuation: Combining Revealed and Stated Approaches.* Vol. 31. New York: Routledge.

Whitehead, John C., Subhrendu K. Pattanayak, George L. Van Houtven, and Brett R. Gelso. 2008 Combining revealed and stated preference data to estimate the nonmarket value of ecological services: an assessment of the state of the science. *Journal of Economic Surveys* 22(5): 872-908.

Figure 1. Southeast Alaska Fishing Locations.

Table 1. Sample characteristics.

Variable	Mean	Std dev	Min	Max
Male	0.67		0	1
Age	46.56	13.67	18	84
Fishing experience	22.98	13.97	0	70
Income ($1000s)	80.33	45.61	5	200
Household size	2.28	1.46	1	11
Trips	11.89	10.06	1	50

Table 2. Revealed preference data.

Alternative	Total Sum	Total %	Typical Sum	Typical %	Travel Cost Mean	Travel Cost Std dev	Halibut Catch Mean	King Salmon Catch Mean	Silver Salmon Catch Mean
Glacier Bay	46	1.9%	4	2.0%	125.68	46.95	0.690	0.050	0.222
Haines-Skagway	76	3.1%	8	3.9%	129.58	59.07	0.066	0.093	0.042
Juneau	997	41.1%	87	42.6%	39.00	38.14	0.173	0.114	0.440
Kake	9	0.4%	2	1.0%	102.04	20.91	0.598	0.110	0.071
Ketchikan	407	16.8%	30	14.7%	123.93	44.34	0.208	0.135	0.445
Petersburg	120	4.9%	13	6.4%	98.96	27.14	0.500	0.179	0.092
Prince of Wales Island	250	10.3%	18	8.8%	145.55	60.05	0.645	0.227	0.734
Sitka	397	16.4%	31	15.2%	147.10	30.57	0.481	0.424	0.596
Wrangell	78	3.2%	9	4.4%	108.24	35.07	0.200	0.312	0.051
Yakutat	45	1.9%	2	1.0%	191.74	59.49	0.559	0.360	0.010

Table 3. Stated preference data.

Alternative	Total Sum	Total %	Travel Cost Mean	Travel Cost Std dev	Halibut Catch Mean	Halibut Catch Std dev	King Salmon Catch Mean	King Salmon Catch Std dev	Silver Salmon Catch Mean	Silver Salmon Catch Std dev
Choice A	104	51%	77.82	44.61	0.91	0.99	0.94	0.87	1.29	1.51
Choice B	81	40%	71.45	24.99	0.85	0.82	0.63	0.77	1.30	1.82
No trip	19	9%	0	0	0	0	0	0	0	0
Choice A	88	43%	75.245	39.62	0.89	0.77	0.58	0.71	1.71	2.25
Choice B	99	49%	114.95	32.5	1.15	0.87	0.77	0.80	1.27	1.32
No trip	17	8%	0	0	0	0	0	0	0	0
Choice A	77	38%	97.43	42.51	0.485	0.698	0.93	0.86	0.21	0.76
Choice B	108	53%	77.45	45.55	0.78	0.88	1.18	1.00	0.90	1.68
No trip	19	9%	0	0	0	0	0	0	0	0
Choice A	111	54%	87.38	43.58	0.50	0.80	1.36	0.77	0.69	1.31
Choice B	70	34%	83.33	31.65	0.71	0.98	0.61	1.01	1.87	2.09
No trip	23	11%	0	0	0	0	0	0	0	0

Table 4. Separately estimated RP and SP models.

	MNL - RP			MXL - SP		
	Coeff.	S.E.	z	Coeff.	S.E.	z
Halibut	0.708	0.600	1.18	0.865	0.144	6.01
King salmon	7.707	1.041	7.40	0.772	0.123	6.28
Silver salmon	0.577	0.486	1.19	0.017	0.054	0.32
Travel cost	-0.051	0.004	-12.58	-0.003	0.002	-1.63
No trip x income				-0.013	0.003	-4.90
Halibut std dev				1.280	0.181	7.09
King salmon std dev				0.925	0.161	5.74
Silver salmon std dev				0.286	0.100	2.87
Cases		204			204	
Periods		1			4	
Model χ^2		116			456	
AIC/n		1.669			1.658	
Pseudo-R^2		0.08			0.25	

Table 5. Scaled models.

	Nested Logit "Trick"			MXL - ECM		
	Coeff.	S.E.	z	Coeff.	S.E.	z
Halibut	0.732	0.253	2.90	0.591	0.049	11.99
King salmon	7.446	0.448	16.64	0.634	0.048	13.23
Silver salmon	0.782	0.161	4.85	0.223	0.030	7.41
Travel cost	-0.042	0.001	-30.95	-0.024	0.001	-32.98
No trip x income	-0.332	0.063	-5.27	-0.053	0.007	-7.05
Standard deviations of random coefficients						
Halibut				0.027	0.119	0.23
King salmon				0.253	0.084	3.02
Silver salmon				0.074	0.081	0.91
Scale (σ)[a]	21.028	2.848	7.38			
Scale-1 [b]				0.626	0.114	5.48
Scale-2 [b]				0.121	0.245	0.49
Scale-3 (no trip) [b]				3.081	0.468	6.58
Cases		204			204	
Periods		8			8	
Model χ^2		3012			2347	
AIC/n		3.24			3.71	
Pseudo-R^2		0.36			0.28	

[a] The relative scale factor in a stacked data

[b] Zero mean SP alternative specific constant scale parameters

Table 6. Naïve scaled and mixed logit RPSP models.

	SMNL			MXL		
	Coeff.	S.E.	z	Coeff.	S.E.	z
Halibut	2.362	0.348	6.79	1.569	0.179	8.78
King salmon	2.797	0.394	7.10	2.138	0.257	8.33
Silver salmon	0.540	0.097	5.58	0.465	0.084	5.53
Travel cost	-0.049	0.006	-7.91	-0.040	0.001	-30.22
No trip x income	-0.053	0.010	-5.55	-0.050	0.004	-12.19
Standard deviations of random coefficients						
Halibut				1.924	0.188	10.24
King salmon				2.727	0.250	10.90
Silver salmon				0.710	0.117	6.10
τ	0.964	0.109	8.840			
σ_i mean	1.000					
σ_i std dev	1.240					
Cases		204			204	
Periods		4			8	
Model χ^2		4087.00			4393.07	
AIC/n		2.108			1.923	
Pseudo-R^2		0.544			0.585	

Table 7. Generalized multinomial logit RP and SP models.

	Naïve GMXL-I			GMXL-I-SP		
	Coeff.	S.E.	z	Coeff.	S.E.	z
Halibut	1.852	0.243	7.63	1.702	0.181	9.38
King salmon	2.532	0.318	7.95	2.941	0.312	9.43
Silver salmon	0.582	0.092	6.30	0.637	0.100	6.35
Travel cost	-0.039	0.001	-29.53	-0.040	0.001	-29.74
No trip × income	-0.051	0.004	-13.87	-0.055	0.004	-13.96
Standard deviations of random coefficients						
Halibut	1.465	0.235	6.24	1.836	0.248	7.40
King salmon	1.888	0.300	6.29	2.026	0.348	5.82
Silver salmon	0.556	0.112	4.95	0.622	0.121	5.16
τ	1.092	0.058	18.76	0.50		
γ	1.00			1.00		
SP (θ)				0.853	0.054	15.85
σ_i mean	0.97			0.98		
σ_i std dev	1.26			1.04		
Cases	204				204	
Periods	8				8	
Model χ^2	4440				4429	
AIC/n	1.896				1.902	
Pseudo-R^2	0.591				0.589	

Table 8. Willingness to pay per fish caught and kept ($).

	Halibut			King salmon			Silver salmon		
Model	WTP	95% C. I.		WTP	95% C. I.		WTP	95% C. I.	
MNL - RP	13.97	-8.41	36.36	152.15	116.33	187.96	11.39	-8.30	31.08
MXL - SP	308.61	-58.74	675.96	275.72	-54.60	606.03	6.03	-30.63	42.69
NL "Trick" - RPSP	17.55	6.13	28.97	178.40	161.77	195.03	18.74	10.62	26.87
MXL - ECM - RPSP	24.85	20.88	28.82	26.66	22.44	30.89	9.38	6.88	11.88
SMNL - RPSP	48.06	42.17	53.96	56.92	48.66	65.18	10.98	8.18	13.78
MXL - RPSP	39.44	31.11	47.77	53.77	41.39	66.14	11.70	7.55	15.84
GMXL - RPSP ($\tau, \theta = 0$)	47.37	35.61	59.12	64.76	48.81	80.70	14.88	10.23	19.52
GMXL - RPSP ($\tau\ fixed, \theta$)	42.02	33.82	50.23	72.62	57.72	87.52	15.73	10.85	20.60