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State dependence and heterogeneity in fishing location choice

Martin D. Smith*

Nicholas School of the Environment and Earth Sciences, Duke University, Box 90328, Durham, NC 27708, USA

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Abstract

To explore the distinction between state dependence and heterogeneity in repeated decisions, this paper combines a Mixed Logit model with a state dependence parameterization from the marketing literature to study fishing location choices of commercial sea urchin divers in California. It examines implications of ignoring either effect and finds in all cases that true state dependence is an important determinant of location choice. Consequently, spatial policies like marine reserves can lead to differences in the short- and long-run behavioral responses of the fishing fleet. Under some specifications, random preference parameters are statistically significant when state dependence is excluded from the model, but when it is included, random preference parameters are not significant. In other specifications, including state dependence only dampens the variability in preference parameters. These results highlight the importance of gathering and analyzing diary-type data for commercial fisheries as well as for similar choice problems in recreation demand.

JEL Classification: C25; Q22; Q26

Keywords: State dependence; Preference heterogeneity; Location choice; Mixed Logit

1. Introduction

Similar individuals facing the same set of choices often make different choices. Explaining this phenomenon has long interested economists and other social scientists. One explanation is that

*Fax: +919 684 8741.
E-mail address: marsmith@duke.edu.

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so-called similar individuals are in fact quite heterogeneous in that they have differing unobservable tastes in spite of the fact that their observable characteristics are the same. Another explanation is that these individuals do have the same basic tastes but have heterogeneous past experiences, and these experiences shape their assessment of future choices. Although a combination of both explanations may characterize many situations, these two approaches to individual behavior have very different econometric modeling implications.

In his seminal work on labor supply, Heckman argues that *heterogeneity* and *true state dependence* are distinct behavioral forces that drive the tendency for individuals to experience the same events repeatedly [15]. Heckman defines heterogeneity as individual differences in ''unmeasured variables'' and explains that ''previous experience may appear to be a determinant of future experience solely because it is a proxy for temporally persistent unobservables'' (pp. 91–92). On the other hand, true state dependence emerges when ''past experience has a genuine behavioral effect in the sense that an otherwise identical individual who did not experience the event would behave differently in the future than individuals who experienced the event'' (p. 91). A key implication of Heckman's paper is that researchers may falsely attribute correlated choices to true state dependence if they fail to model heterogeneity. That is, they may conclude that past events cause future events when the actual causal connection between past and future choices is through unobservables that are correlated over time.

Although the state dependence and heterogeneity distinction has substantial policy implications, econometric models that incorporate both effects are rare. This dearth of empirical work reflects both the computational difficulty of these problems, and perhaps more importantly, a lack of appropriate data sets.[1] To model state dependence, one needs many repeated choices of the same agents. However, to study heterogeneity, one needs many agents. Such long and wide panels are rarely available. Typically, the events of interest are discrete, the corresponding econometric model takes some multinomial form, and the likelihood function has no closed-form expression. As a result of computational and data limitations, most researchers ignore either state dependence or heterogeneity, and in many cases, researchers ignore both in favor of a representative agent model.

Recent advances in simulation-based estimation combined with the expansion of computing power have made it possible to entertain elaborate models of heterogeneity [14,24,27]. Combining parameter heterogeneity with dynamic processes creates additional complications. Lee [22] assesses the performance of simulated maximum likelihood estimation of Heckman [16] dynamic discrete binary choice models with a Monte Carlo study. Lee finds that most of these models can be estimated well with a moderate number of simulations and with reasonably long panels (between 30 and 50). Perhaps most importantly, simulated maximum likelihood with long panels performs better for models that account for longer histories of past choices, e.g. Polya and Renewal, than for models based only on the immediate past, e.g. Markov.

Since these advances clearly do not address data availability problems, it is perhaps not surprising that researchers have responded with a number of studies that explore heterogeneous preferences in discrete choice models but that leave out state dependence. This trend raises an important question: if the data necessary to examine state dependence are unavailable, what are

[1] Heckman [16] introduces a variety of dynamic discrete choice models in the context of binary choice. This paper considers a hybrid of two of these in the context of multinomial choice.

the implications of modeling heterogeneity in isolation? In an exception to this trend that empirically models state dependence and heterogeneity, Keane employs supermarket scanner data to construct a long and wide panel of repeated household product choices [20]. Applying a multinomial probit model that includes state dependence and random parameters to represent taste heterogeneity, he finds evidence of both effects while reflecting the computational challenges of this type of work. Keane's results point to the potential importance of state dependence and heterogeneity in other multinomial choice settings.

A significant empirical application of state dependence and heterogeneity that has not previously been explored is modeling location choice. Location choices are often discrete and serially correlated events. Variation in tastes for attributes of different location choices is one form of heterogeneity in this setting and will be termed *preference heterogeneity* throughout the remainder of this paper. True state dependence may emerge for a variety of reasons. However, one particularly plausible explanation in location choice is that individual experiences of locations shape their information sets in a manner that gives rise to heterogeneous expectations about the future value of choosing that location [32]. Although this information effect illustrates the subtle difference between state dependence and heterogeneity, it fits squarely into Heckman's definition of true state dependence.

Location choice figures into many economic analyses but is a fundamental empirical problem in environmental and resource economics. For example, location choice is arguably the most important behavioral driver in revealed preference non-market valuation. In hedonic studies of environmental quality change, the underlying location choices of agents are used to resolve the hedonic price function [11]. In recreation demand, empirical models of location choice are used to estimate welfare effects from changes in site quality [4]. In renewable resource economics, spatial modeling has become significant research focus in recent years [7]. Understanding and explaining spatial patterns of resource exploitation often involve location choice models, particularly in fisheries [10]. With the recent emphasis on management with spatially explicit tools, understanding fishing location choice has taken on an even greater significance because spatial behavior of fishermen is a critical determinant of fisheries policy outcomes. Location choice models are used to examine the long-run bioeconomic impacts of fisheries policies [35,43]. When bioeconomic models account for spatial behavior, they reach dramatically different conclusions about the efficacy of marine reserves from models that ignore spatial behavior [34,35]. Spatial behavior even affects the performance of policies that are not spatially delineated such as size limits [43].

This paper combines a Mixed Logit [24] model with a state dependence parameterization from the marketing literature on brand loyalty [13] to study repeated fishing location choices of commercial sea urchin divers in California. The Mixed Logit specification represents preference heterogeneity with random parameters, and the econometric model uses simulation-based estimation. The paper examines whether either preference heterogeneity or true state dependence can be restricted out of the model and the implications of ignoring one or the other. In all cases, true state dependence is an important determinant of location choice. Under some specifications, random preference parameters are statistically significant when state dependence is excluded from the model, but when it is included, random preference parameters are not significant. In other specifications, including state dependence only dampens the variability in preference parameters. Although the focus of this paper is modeling location choice in a commercial fishery, the results are directly transferable to a recreation demand site choice problem because the recreation demand choice structure is isomorphic. As such, this paper questions how much preference heterogeneity that is found in some recreational site choice models is attributable to preferences and how much is a reflection of heterogeneous experience. The results ultimately highlight the importance of gathering and analyzing diary-type repeated choice data for commercial fisheries and recreation demand site choice studies.

The remainder of this paper is organized as follows. Section 2 reviews repeated location choice models in commercial fisheries and recreation demand and develops an econometric model with state dependence and preference heterogeneity. Section 3 provides background on the California sea urchin fishery and describes the data set used in this paper. Section 4 details the estimation procedure and presents the empirical results. Finally, Section 5 discusses the implications of these findings.

2. An econometric model of state dependence and preference heterogeneity

In commercial fisheries, harvesters make repeated choices about where to fish. A key insight for understanding these choices is that biological resources are often "patchy" and occur in discrete clumps [30]. In a patchy setting, breaks in habitat generate discontinuities in the spatial structure such that harvest decisions are reasonably modeled as discrete choices among a finite set of fishing locations. For this reason, a Random Utility Model has been the common approach to modeling spatial decisions in commercial fisheries [5,10,19,25,33].[2] The results of discrete choice fisheries models are consistent across studies but leave substantial variation in spatial behavior unexplained. Studies generally find that higher expected revenues (ER) increase the probability of visiting a site, greater travel distances decrease this probability, and site-specific constants have considerable explanatory power.

A difficulty in studying discrete spatial choices is that harvesters typically exhibit behavioral heterogeneity; apparently similar individuals frequently choose different alternatives. For instance, some individuals starting from the same fishing port visit one fishing ground, while others starting from the same port on the same day visit a different fishing ground. True state dependence and preference heterogeneity provide different explanations for this phenomenon.[3] Bockstael and Opaluch [5] find that state dependence adds substantial explanatory power to a model of fishery choice from season to season. This suggests that the fishing fleet responds sluggishly to changes in expected returns over space. On finer spatial and temporal scales, namely repeated choice of fishing grounds, several authors find evidence of temporally autocorrelated spatial behavior that could be due to true state dependence [19,36]. However, they neither model unobserved heterogeneity that is temporally persistent (i.e. a random effect) nor unobserved preference heterogeneity (i.e. random parameters). Another study finds some evidence of preference heterogeneity but without controlling for state dependence [25]. Given the importance

[2]Though not specifically about choice of a fishing ground, Bockstael and Opaluch provided the first application of discrete choice to commercial fisheries and laid the groundwork for subsequent papers to explore location choice [5]. Their model analyzes the choice of in which fishery to participate and includes a combination of species and broad geographical region.

[3]Although the focus here is on state dependence and heterogeneity, it is important to note that other explanations are possible such as congestion effects.

of sluggish adjustment in dynamic bioeconomic models, one naturally might ask whether all of these findings are robust when both unobserved preference heterogeneity and state dependence are controlled for as Heckman [15] emphasizes in a binary choice setting.

In recreation demand, individuals face similar repeated discrete location choices [26]. While potential for income effects and preference for variety adds complications to the recreation problem, the basic choice structure is the same as in commercial fisheries. Individuals may have heterogeneous preferences over site attributes, but they almost certainly have heterogeneous information about site quality based on their personal experiences. Thus, there are compelling reasons to examine both state dependence and preference heterogeneity jointly. No one has estimated a model with both effects arguably because very few recreation demand panel data sets exist that could support such a model. One study formally accounts for the influence of past choices on future ones in a standard RUM framework but does not include taste heterogeneity [1]. Another study proposes a dynamic Generalized Extreme Value model to address state dependence in recreation demand models [38] and finds large differences between welfare measures based on a static model and measures based on models that account for state dependence. However, this work does not include taste heterogeneity. An alternative to the static RUM framework is to pose a fully dynamic model of recreation behavior that includes forward-looking behavior [29]. Such an approach is so computationally intensive that parameterizing taste heterogeneity is potentially unmanageable.

Several recent studies parameterize taste heterogeneity using a random-parameters structure but do not formally model state dependence [6,9,18,39].[4] These models do not separately identify taste heterogeneity and information heterogeneity, as argued in [32]. A recent recreation demand study models taste heterogeneity with serially correlated errors but does not examine the direct influence of past choices on future ones [28]. Since there are currently limited opportunities to explore state dependence and heterogeneity in recreation demand, an isomorphic commercial fisheries application can shed light on how important these issues may be.

Models of discrete location choice—whether they be in commercial fisheries or recreation demand—usually employ some version of McFadden's model of random utility maximization (RUM) [23]. A RUM contains a systematic component of utility, typically assumed common to all individuals in the data set, and a random component of utility, which varies across individuals. This approach to some extent accounts for the empirical phenomenon that we as analysts see, namely that two individuals with the same observable characteristics and opportunities sometimes choose two different discrete alternatives. As a method for modeling discrete repeated decisions of individual economic agents, the basic conditional logit model incorporates a form of heterogeneity in the sense that there is a random component, but this error is independent across individuals and time. Thus, it does not capture time-invariant individual taste heterogeneity.

This paper uses a Mixed Logit model [24] with a linear indirect utility function to capture taste heterogeneity. The development of the model follows the treatment in Train [39] but with different notation to customize the problem. Let i index individuals, j locations, and t choice occasions.

[4] Random parameters for taste heterogeneity in a discrete choice model have also been applied to stated preference data [21]. In this context, the potential role of state dependence seems less significant. One could explore this issue in an experimental setting.

Agent i's utility from going to site j on choice occasion t is

$$U_{ijt} = \mathbf{X_{jt}\beta_i} + \varepsilon_{ijt}, \tag{1}$$

where $\mathbf{X}$ denotes choice-specific characteristics such as travel costs and ER (arising from spatial variation in resource abundance and quality), $\boldsymbol{\beta}_\mathbf{i}$ is a parameter vector that varies across individuals, and ε_{ijt} is a random component that is unobservable to the analyst. Note that $\mathbf{X}$ varies across choices and time but not across individuals because we do not directly observe individual information sets. The individual is presumed to select the alternative with the highest utility from M possible choices. Assuming that ε_{ijt} is distributed IID Type I Extreme Value and $\boldsymbol{\beta}_\mathbf{i} \sim MVN(\bar{\boldsymbol{\beta}}, \boldsymbol{\Omega})$, the individual choice probabilities involve the logit probabilities nested within a multivariate normal integral:

$$p_{ikt} = \int \frac{\exp(\mathbf{X_{kt}\beta})}{\sum_{j=1}^{M} \exp(\mathbf{X_{jt}\beta})} \phi(\boldsymbol{\beta}|\bar{\boldsymbol{\beta}}, \boldsymbol{\Omega})\, d\boldsymbol{\beta}. \tag{2}$$

Although this integral cannot be solved explicitly, the insight of simulation-based estimation is that it can be well approximated through Monte Carlo simulation of the probabilities and averaging across R total random draws. Each draw from the multivariate normal produces a simulated probability $\tilde{p}^{r}_{ijt}$, and these draws then are averaged to produce a simulated likelihood:

$$SL = \prod_{i} \prod_{t} \frac{1}{R} \sum_{r=1}^{R} \tilde{p}^{r}_{ikt}. \tag{3}$$

Simulated maximum likelihood proceeds by maximizing the log of (3).

Modeling state dependence introduces a form of heterogeneity even when the distribution of $\boldsymbol{\beta}_\mathbf{i}$ is degenerate. For purposes of explanation, suppose that there are just two covariates that affect location choices: state dependence (x^{SD}_{ijt}) and "other" (x^{O}_{jt}). State dependence is individual-, location-, and time-specific, whereas "other" does not vary across individuals. We rewrite (1) as

$$U_{ijt} = \beta_{\mathrm{O}} x^{\mathrm{O}}_{jt} + \beta_{\mathrm{SD}} x^{\mathrm{SD}}_{ijt} + \varepsilon_{ijt}. \tag{4}$$

Define a binary variable y_{ijt} to indicate whether an individual visited a patch at time t:

$$y_{ijt} = \begin{cases} 1 & \text{if } i \text{ visited } j \text{ at } t, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The state dependence variables follow a procedure developed in Gaudagni and Little [13] and used in conjunction with random parameters by Keane [20].[5] State dependence evolves according to the following:

$$x^{\mathrm{SD}}_{ijt} = \alpha x^{\mathrm{SD}}_{ijt-1} + (1-\alpha) y_{ijt-1}. \tag{6}$$

Thus, the state dependence for this period's decision is a convex combination of the previous period's decision and a geometrically decaying summary of all previous decisions associated with

[5]This approach to state dependence is similar in spirit to the series of dummy variables used in [19] but has several advantages. First, it permits a smooth relationship between past and present decisions. Second, past information is never truncated after a certain period of time. Finally, it is more parsimonious in that is requires fewer parameters to capture the essential components of state dependence (excluding initial conditions).

that location. In that sense, α operates like a discount factor. If an individual always visits the same place, the state dependence variable for that place asymptotes to one, and all others go to zero. A single visit by an individual to a location, never returning, will continue to influence the individual's behavior throughout the sample period but in a way that decreases geometrically over time.

For each individual at $t = 1$, a set of initial conditions, $\tilde{x}_{ij1}^{SD}$, where $i = 1, \ldots, N$ and $j = 1, \ldots, M$, determines the subsequent evolution of the state dependence variables. Substituting the initial conditions into (6), the first three periods of state dependence are

$$x_{ij1}^{SD} = \tilde{x}_{ij1}^{SD},$$
$$x_{ij2}^{SD} = \alpha\tilde{x}_{ij1}^{SD} + (1-\alpha)y_{ij1}, \quad \text{and} \quad x_{ij3}^{SD} = \alpha[\alpha\tilde{x}_{ij1}^{SD} + (1-\alpha)y_{ij1}] + (1-\alpha)y_{ij2}. \tag{7}$$

By defining a time index τ, this recursive process after the first period is

$$x_{ijt}^{SD} = \alpha^{t-1}\tilde{x}_{ij1}^{SD} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{ij\tau-1}. \tag{8}$$

Substituting (8) into (4), the utility function is now

$$U_{ikt} = \beta_O x_{kt}^O + \beta_{SD}\left[\alpha^{t-1}\tilde{x}_{ik1}^{SD} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{ik\tau-1}\right] + \varepsilon_{ikt}. \tag{9}$$

Substituting (9) into the probability for a conditional logit model and assuming exogenous initial conditions (this issue will be addressed in the next section), we have a closed form expression for the likelihood, albeit a highly non-linear one:

$$p_{ikt} = \frac{\exp(\beta_O x_{kt}^O + \beta_{SD}[\alpha^{t-1}\tilde{x}_{ik1}^{SD} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{ik\tau-1}])}{\sum_{j=1}^{M}\exp(\beta_O x_{jt}^O + \beta_{SD}[\alpha^{t-1}\tilde{x}_{ij1}^{SD} + (1-\alpha)\sum_{\tau=2}^{t}\alpha^{t-\tau}y_{ij\tau-1}])}. \tag{10}$$

Thus, with a degenerate distribution on β, one can use maximum likelihood to find the parameters β_{SD}, β_O, and α.

Compared to the models in Heckman [16] and Lee [22], the Guadagni and Little [13] state dependence model is a hybrid of the Polya model and a first-order Markov model. At one end of the α parameter space, the state dependence portion of indirect utility reduces to a first order Markov process. Specifically, the state dependence portion of indirect utility is $\beta_{SD}x_{ijt}^{SD}$. When $\alpha = 0$, $\beta_{SD}x_{ijt}^{SD} = \beta_{SD}y_{ijt-1}$. At the other end of the parameter space, α approaches 1, and only the geometrically decaying summary of all past choices is left. Thus, as α approaches 1, the recent past matters less and less, and the model is nearly a pure Polya model. However, when $\alpha = 1$, it does not collapse to the pure Polya model because there is no decay of past activity left, and the total number of past choices in that area is what affects current choice. Table 1 shows three different 10-choice sequences for a location and computes the state dependence variable for three different values of α. When there are several consecutive occasions in which an agent chooses the same location, α controls the speed at which state dependence ramps up and ramps down. When choices alternate, the higher value of α dampens oscillations in the state dependence variable. Thus, in all of these cases α is a smoothing parameter.

Table 1
The effect of choice sequences on state dependence variables

t	Choice	$\alpha = 0.1$ x^{SD}	$\alpha = 0.5$ x^{SD}	$\alpha = 0.9$ x^{SD}	Choice	$\alpha = 0.1$ x^{SD}	$\alpha = 0.5$ x^{SD}	$\alpha = 0.9$ x^{SD}	Choice	$\alpha = 0.1$ x^{SD}	$\alpha = 0.5$ x^{SD}	$\alpha = 0.9$ x^{SD}
1	1	0.000	0.000	0.000	0	0.000	0.000	0.000	1	0.000	0.000	0.000
2	1	0.900	0.500	0.100	0	0.000	0.000	0.000	0	0.900	0.500	0.100
3	1	0.990	0.750	0.190	0	0.000	0.000	0.000	1	0.090	0.250	0.090
4	1	0.999	0.875	0.271	0	0.000	0.000	0.000	0	0.909	0.625	0.181
5	1	1.000	0.938	0.344	0	0.000	0.000	0.000	1	0.091	0.313	0.163
6	0	1.000	0.969	0.410	1	0.000	0.000	0.000	0	0.909	0.656	0.247
7	0	0.100	0.484	0.369	1	0.900	0.500	0.100	1	0.091	0.328	0.222
8	0	0.010	0.242	0.332	1	0.990	0.750	0.190	0	0.909	0.664	0.300
9	0	0.001	0.121	0.299	1	0.999	0.875	0.271	1	0.091	0.332	0.270
10	0	0.000	0.061	0.269	1	1.000	0.938	0.344	0	0.909	0.666	0.343
11		0.000	0.030	0.242		1.000	0.969	0.410		0.091	0.333	0.309

The state dependence model in (6) is a sensible one to describe fishing location choice for several reasons. First, it captures the cumulative effect of experience in an area. There may be learning that takes place with regard to fish finding or dealing with currents and tides that is additive. Second, because of biological dynamics and continuous harvesting of the resource, information about fish abundance will decay, and experience in the recent past undoubtedly matters more than experience in the distant past. Finally, though the ordinal pattern is assumed, the magnitudes of influence from the distant and recent past are estimated. Thus, this model is flexible enough to accommodate other fisheries, both recreational and commercial.

3. Empirical setting and data

This work draws on a data set that was constructed to trace participation and location choice behavior in the northern California sea urchin fishery. The complete data set tracks the daily decisions of about 1000 harvesters over a 10-year period. The data set used in this paper consists of daily observations on individual California sea urchin divers from 1988–1997, including departing port location, diving location, and revenues. The focus is on the northern California fishery, since regulators have shown more concern about its potential collapse than the southern California fishery, and as a result, future spatial management in the north is likely.

The structure of the sea urchin fishery allows us to explore state dependence and preference heterogeneity through repeated location choices. As a dive fishery composed mostly of owner-operators, fishing equipment and skills are not easily substituted into other fisheries. Moreover, there is virtually no variation in observable characteristics because vessels and gear are nearly uniform across divers. In this fishery, harvesters make day trips from each of four northern California ports to locations offshore in waters up to 60-ft deep. Thus, choice occasions are easy to define, avoiding complications of multi-day trips that might occur in other fisheries. Connected through a hookah to an air compressor on the vessel, harvesters dive for the urchins, scrape them from the bottom using hand-held rakes, collect them in mesh bags, and then deliver the urchins to processing facilities at the port of landing. Urchins are processed immediately, packaged, and shipped to the Tokyo Central Wholesale Market for sale in the fresh market. The data are divided into eleven geographically distinct harvest zones or patches. The patches are not of equal size, but instead they reflect spatial breaks in harvest activity that suggests natural divisions between patches [33]. With the exception of patch 0 (the Farallon Islands), all patches are contiguous along the northern California coast, beginning in Half Moon Bay and stretching north to the Oregon border. Thus, the relevant spatial choices can be thought of as occurring in one dimension rather than in two.

The empirical analysis uses all of the observations for each of 50 randomly sampled divers who fished for urchins at least ten times between 1988 and 1997.[6] The minimum number of observations for an individual is thus ten, while the theoretical maximum is 2629, the total number of open season days for sea urchins over this interval. In practice, weather conditions, market conditions, and fatigue limit the number of dive occasions. In the 50-diver sample, the actual minimum, maximum, and mean number of dives over the sample period are 10, 617, and 160.64, respectively. The total number of observations is 8032.

Within the sample, there is considerable variation in the amount of spatial mobility that harvesters exhibit. In each port on each diving day, there are generally 3–4 patches within feasible travel distance that a given diver might access. Over the season or between seasons, divers may switch home ports and gain access to other combinations of patches along the coast. In the sample of 50 divers, two visit as few as one patch, while two others visit nine patches over the whole sample period. The average (non-weighted) number of patches visited is 5.18. The median is 5.5. By weighting according to each diver's total number of dives, the weighted average number of patches visited is 6.14.

One can also compute a spatial coefficient of variation for each diver in the sample and examine the distribution of these coefficients to study spatial mobility. For each diver the mean patch number and the standard deviation of patch numbers are computed, and the coefficient of variation is the ratio of the standard deviation to the mean.[7] To explain the intuition behind this statistic, consider the following hypothetical example. Suppose Diver A visits patch 5 six times and never goes to any other patch. Suppose also that Diver B visits patch 5 four times, patch 6 once, and patch 4 once, and Diver C visits patch 5 twice, patch 6 twice, and patch 4 twice. In this example, the average spatial location of each diver is the same, but the variance in patch numbers reflects different levels of mobility. For this example, the spatial coefficients of variation would be 0, 0.13, and 0.18 for A, B, and C, respectively. Fig. 1 is a histogram of the results from the 50-diver sample. The distribution is centered and peaks at a low to moderate level of mobility, though the right tail indicates that some divers exhibit a high degree of spatial mobility.

[6]A portion of the data is used rather than the full data set because the computational requirements of Mixed Logit combined with state dependence and initial conditions estimation are substantial.

[7]This measure is not perfectly unit-free because the center of an individual's spatial activity affects the coefficient of variation. However, it is indicative of varying degrees of mobility.

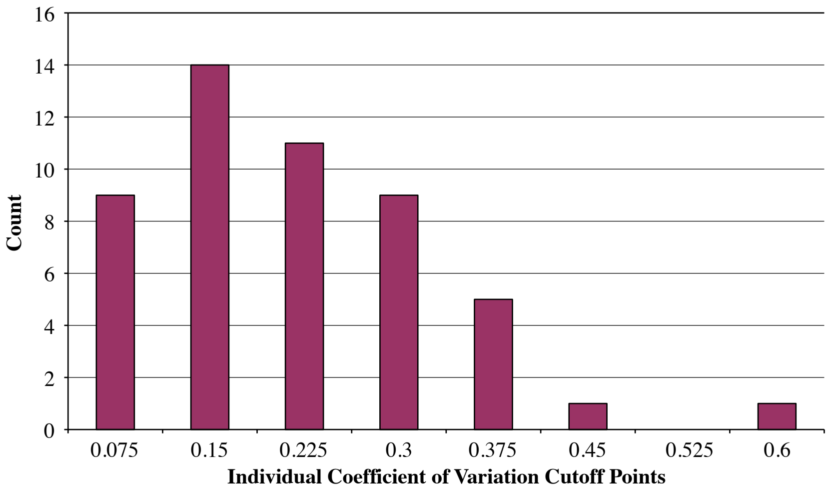

Fig. 1. Distribution of spatial coefficients of variation.

4. Estimation and results

Following the spatial rent-arbitraging hypothesis of Sanchirico and Wilen [30] and the discrete choice literature on commercial fisheries, expected returns in different locations drive harvester choices. These returns are unobservable, but differences across space are largely due to differences in travel costs and differences in ER. The variable distance (DIST) proxies for travel costs and measures the distance from each port to the center of each patch. Since each diver's port on each choice occasion is observable, it is simple to generate the full set of possible travel distances to each patch. In contrast, there are numerous conceptual and practical complications involved in computing ER in this setting [32]. This model uses the product of expected price and expected catch per trip, computed over the entire data set (not just the 50-diver sample). The former is a 1-month backward looking rolling average across all sites in northern California, while the latter is computed in the same fashion but is site-specific across each of the eleven patches.

Estimation of the full model entails three complications. First, the state dependence variables that enter the indirect utility function are dependent on the parameter α (and on initial conditions). Second, the initial conditions on the state dependence variables must be estimated in some way. Finally, the Mixed Logit specification requires simulation-based estimation because a closed form solution does not exist for the likelihood function.

The first issue—the dependence of x^{SD}'s on the α smoothing parameter—is not an econometric problem per se but simply a complication in coding the likelihood function. The indirect utility in (9) is non-linear in the parameters. Thus, the maximum likelihood routine (or simulated maximum likelihood for random parameters models) must loop over past choices and the current value of α to generate x^{SD}'s, which are then multiplied by β_{SD} in the indirect utility portion of the likelihood. This is easily accomplished but adds computational time because matrix programming languages like GAUSS are optimized for vector and matrix operations. At each iteration of the maximum likelihood routine, the need to run through a scalar loop slows down the program considerably.[8]

The second complication of estimating the initial conditions on state dependence variables has long been a difficult problem in dynamic discrete choice models. This paper assumes that the initial conditions are strictly exogenous, which means that they can be treated parametrically. Heckman [17] cautions against doing this in a dynamic discrete choice model unless the analyst observes the entire process from the beginning. However, in this setting we actually do observe the process from the beginning for most of the individuals in the sample. The northern California fishery was virtually non-existent before 1988, which is the same time that the logbook program was initiated. Thus, most of the divers in northern California entered after diary record keeping began. Of the 50 individuals in the sample, only six record their first landing before April 1988. So at most, six out of 50 were fishing prior to what we observe. Moreover, with many choice occasions per cross-sectional unit, the law of large numbers to some extent can ameliorate the initial conditions problem [12].

With 50 individuals, assuming exogenous initial conditions still causes problems because it leads to an incidental parameters problem.[9] To simplify matters, this paper assumes that the set of initial conditions is invariant across individuals. We find in the results that the initial conditions in aggregate are not jointly significant, but it is worth noting the caveat that this result could partly reflect the fact that fixed initial conditions across individuals introduces more noise than explanatory power. Finally, Eq. (6) requires that these conditions lie in the (0,1) interval. Thus, the estimation employs a logistic transformation to the base initial condition parameters in order to generate the true initial conditions. Denoting the eleven base parameters θ_j, the utility function in (9) with no random parameters is

$$\begin{aligned} U_{ikt} = {} & \beta_k + \beta_{\mathrm{ER}} x_{kt}^{\mathrm{ER}} + \beta_{\mathrm{DIST}} x_{kt}^{\mathrm{DIST}} \\ & + \beta_{\mathrm{SD}} \left[\alpha^{t-1} \frac{\exp(\theta_k)}{1+\exp(\theta_k)} + (1-\alpha) \sum_{\tau=2}^{t} \alpha^{t-\tau} y_{ik\tau-1} \right] + \varepsilon_{ikt}, \end{aligned} \tag{11}$$

where β_k denotes a location-specific constant. Again, this is highly non-linear in the parameters, but the corresponding likelihood has a closed form as long as the parameters are fixed across individuals.

Dealing with the complication of random parameters requires simulation-based estimation. Analytically, we substitute the deterministic portion of (11) into (2) and integrate over the random parameters distribution to obtain the likelihood:

$$\begin{aligned} p_{ikt} & \\ = & \int \int \cdots \int \frac{\exp\left(\beta_k + \beta_{\mathrm{ER}} x_{kt}^{\mathrm{ER}} + \beta_{\mathrm{DIST}} x_{kt}^{\mathrm{DIST}} + \beta_{\mathrm{SD}} \left[\alpha^{t-1} \frac{\exp(\theta_k)}{1+\exp(\theta_k)} + (1-\alpha) \sum_{\tau=2}^{t} \alpha^{t-\tau} y_{ik\tau-1} \right] \right)}{\sum_{j=1}^{M} \exp\left(\beta_j + \beta_{\mathrm{ER}} x_{jt}^{\mathrm{ER}} + \beta_{\mathrm{DIST}} x_{jt}^{\mathrm{DIST}} + \beta_{\mathrm{SD}} \left[\alpha^{t-1} \frac{\exp(\theta_j)}{1+\exp(\theta_j)} + (1-\alpha) \sum_{\tau=2}^{t} \alpha^{t-\tau} y_{ij\tau-1} \right] \right)} \\ & \times \phi(\beta_1, \beta_2, \ldots \beta_{M-1}, \beta_{\mathrm{SD}}, \beta_{\mathrm{ER},}, \beta_{\mathrm{DIST}} | \bar{\beta}_1, \bar{\beta}_2, \ldots \bar{\beta}_{M-1}, \bar{\beta}_{\mathrm{SD}}, \bar{\beta}_{\mathrm{ER},}, \bar{\beta}_{\mathrm{DIST}}, \mathbf{\Omega}) \\ & \times d\beta_1 \, d\beta_2 \ldots d\beta_{M-1} \, d\beta_{\mathrm{SD}} \, d\beta_{\mathrm{ER},} \, d\beta_{\mathrm{DIST}}. \end{aligned} \tag{12}$$

[8] GAUSS code is available from the author upon request.

[9] In this setting, estimation would require 550 initial conditions and pose computational difficulties.

Note again that there is no closed-form expression for (12).[10]

We use maximum simulated likelihood to estimate each model. Halton draws are used rather than pure random draws in order to increase numerical efficiency. Compared to pure random draws, Halton draws provide better coverage of the relevant support [41]. For Mixed Logit, 125 Halton draws appear to perform as well as 2000 random draws [2,40,41]. Additional estimation details are available online as a supplement to the paper through the website http://www.aere.org/journal/index.html.

4.1. Heterogeneous responses to structural covariates only

As an initial step, we consider preference heterogeneity only on the structural covariates. As such, the covariance matrix is of the random parameter vector is

$$\Omega = \begin{bmatrix} \sigma^2_{\mathrm{ER}} & \sigma_{\mathrm{ER,DIST}} & 0 & \cdots & 0 \\ \sigma_{\mathrm{DIST,ER}} & \sigma^2_{\mathrm{DIST}} & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}. \tag{13}$$

Thus, there are just three distinct parameters of the random-parameters covariance matrix. This implies that there are three distinct Cholesky factors to estimate as well. While this model is restrictive, it is a sensible starting place for estimating a model with both state dependence and heterogeneity. In contrast to models that allow for more elaborate parameterizations of heterogeneity, such as random effects, we can more readily attach structural interpretation to covariance parameters. The parameter σ^2_{ER} reflects heterogeneity in responsiveness to revenues over space. If this parameter is significant, it suggests that some divers are more actively engaged in spatial arbitraging than others. The parameter σ^2_{DIST} reflects heterogeneity in responsiveness to travel distance. If this parameter is significant, it could indicate variation in opportunity cost of time or differences in aversion to risk of bad weather, i.e. not wanting to be too far from port if the weather changes for the worse.

Table 2 contains raw estimates from four models. That is, it reports mean structural parameters for the covariates ER and DIST, choice-specific constants, the parameter on state dependence in the indirect utility function, Cholesky factors for the random parameters, the α smoothing parameter, and non-transformed initial condition parameters. Model A is the full model in which both state dependence and preference heterogeneity are estimated. Model B restricts the effect of state dependence to zero but still includes preference heterogeneity. Model C maintains state dependence but restricts preference heterogeneity to zero. Finally, Model D restricts both state dependence and preference heterogeneity.

All of the ER and DIST coefficients have their expected signs, making the model consistent with a spatial choice process that maximizes rents over space. For the random parameters models

[10]This model assumes that autocorrelation is captured by the random parameter vector or by the state dependence parameterization. In that sense, it ignores the possibility for autocorrelation in the idiosyncratic error, which is a potential limitation of the analysis.

Table 2
Estimation results from discrete location choice models

	Model A	Model B	Model C	Model D
	Full model	Het., No St. Dep.	St. Dep., No Het.	No St. Dep., No Het.
Heterogeneity in structural covariates only with a multivariate normal distribution				
ER	0.0169 (0.0086)*	0.0605 (0.009)**	0.0163 (0.0082)*	0.027 (0.0069)**
DISTANCE	−7.9078 (0.2482)**	−13.7997 (0.3827)**	−7.889 (0.2223)**	−11.932 (0.2385)**
State Dep.	2.5045 (0.0535)**		2.5033 (0.0532)**	
Patch-specific constants				
Farallons	−0.1583 (0.251)	0.3988 (0.2493)	−0.1747 (0.2424)	−0.324 (0.2349)
Patch 1	0.095 (0.325)	0.9492 (0.2993)**	0.0912 (0.3239)	0.654 (0.2925)*
Patch 2	−4.0228 (0.2692)**	−5.7078 (0.2725)**	−4.0363 (0.2665)**	−6.181 (0.2644)**
Patch 3	−2.7699 (0.2471)**	−3.2259 (0.2502)**	−2.7878 (0.2404)**	−3.966 (0.2447)**
Patch 4	−1.9893 (0.2168)**	−2.2643 (0.2254)**	−2.0103 (0.2041)**	−3.266 (0.2041)**
Patch 5	−2.4345 (0.2304)**	−2.4693 (0.2374)**	−2.4547 (0.2215)**	−3.360 (0.2241)**
Patch 6	−2.8039 (0.2314)**	−3.5491 (0.2427)**	−2.8259 (0.2198)**	−4.559 (0.2236)**
Patch 7	−3.0264 (0.2476)**	−3.8324 (0.2616)**	−3.0478 (0.2388)**	−4.720 (0.2489)**
Patch 8	−4.0993 (0.27)**	−5.5138 (0.2877)**	−4.1181 (0.2657)**	−6.097 (0.2782)**
Patch 9	−2.9936 (0.2409)**	−3.9485 (0.2562)**	−3.0153 (0.2311)**	−4.877 (0.2397)**
Patch 10	0 Restricted	0 Restricted	0 Restricted	0 Restricted
Alpha Smoothing	0.5137 (0.0181)**		0.5137 (0.0181)**	
Non-transformed initial conditions				
Init 0	−4.0697 (31.5838)		−4.0694 (33.4639)	
Init 1	−0.8932 (2.9441)		−0.9024 (2.9687)	
Init 2	−0.2159 (1.6513)		−0.2161 (1.6076)	
Init 3	0.4079 (1.3731)		0.4096 (1.3675)	
Init 4	−5.6711 (22.6531)		−5.6718 (22.6636)	
Init 5	2.5635 (3.1825)		2.5774 (3.2686)	
Init 6	0.9579 (1.1134)		0.947 (1.1125)	
Init 7	1.2038 (0.9987)		1.195 (0.9981)	
Init 8	5.423 (16.5403)		5.4247 (17.146)	
Init 9	1.5148 (1.14359)		1.5115 (1.4385)	
Init 10	−4.6955 (13.712)		−4.6974 (13.6838)	
Cholesky factors				
Cholesky 1	−0.0085 (0.0221)	−0.0467 (0.0089)**		
Cholesky 2	0.0504 (0.37)	0.3747 (0.5717)		
Cholesky 3	0.3729 (0.8638)	3.4259 (0.2674)**		
N	8032	8032	8032	8032
Log-likelihood	−5966.92	−7969.16	−5966.98	−8001.50
Pseudo R^2	0.612	0.482	0.612	0.480
LR tests	Restrict A to C	Restrict B to D	Restrict C to D	Restrict A to D
Chi-square	0.13	64.69**	4069.04**	4069.17**
	Fail to reject	Reject	Reject	Reject

Notes: Standard errors are in parentheses. *Indicates statistically significant at the 5% level, and **indicates significant at the 1% level. Pseudo R^2 is computed as one minus the ratio of a restricted log-likelihood to the log-likelihood from the model reported. The restricted log-likelihood is from a model with just choice-specific constants.

(A and B), the coefficients reported for ER and DIST are the mean values for the random parameters. Across all models, all ER and DIST coefficients are statistically significant. Table 2 also reports patch-specific constants. For identification, the constant in patch 10 is restricted to zero. For the remaining free parameters, eight out of ten are significant in models A and C, while nine out of ten are significant in models B and D. The α smoothing parameter is strongly significant in both models with state dependence and is estimated so precisely that it is virtually indistinguishable in the two models. None of the individual Cholesky factors are significant in Model A, and two of the factors are significant in Model B. None of the non-transformed initial conditions are individually significant. However, these are strange tests because when one of these parameters equals zero, the actual initial condition is $[e^0/(1+e^0)] = 0.5$. The relevant test is for joint significance of the actual initial conditions. The initial conditions are neither jointly significant in Model A ($\chi^2(11) = 14.26$) nor in Model B ($\chi^2(11) = 14.46$). The critical value for the $\chi^2(11)$ at the 5% significance level is 19.68.

Potentially, the most important results in Table 2 are the likelihood ratio tests. First, we reject restricting either Models A to D or C to D, which means that the state dependence variables are jointly statistically significant. Second, we fail to reject restricting the full model to Model C. In other words, the random parameters are not jointly significant in a model that includes state dependence. Thus, preference heterogeneity—at least across the ER and DIST dimensions—does not appear to exist in the sample. However, when we do not model state dependence, as in Model B, we reject the restriction of the random parameters. That is, we reject the restriction of Model B to D. This means that the random parameters appear statistically significant when Model A demonstrates that they are not significant. The lesson here is that potentially spurious preference heterogeneity emerges when state dependence is not modeled.

It is important to put these results in the context of other explorations of fishing heterogeneity with these data. The location choice models all condition on a diver already deciding to take a trip. It may be that heterogeneous responsiveness to exogenous variables only enters the decision of whether to take a trip. After all, once a diver chooses to take a trip, it is in the diver's interest to maximize returns from the trip. Why would we expect balancing of revenues and travel costs to vary systematically across the fleet? Heterogeneity in outside opportunities and differences in risk preferences, on the other hand, may affect the decision of whether to fish on any given day. In models of trip choice based on individual-level estimates using this data set, it appears that such heterogeneity does exist in this fleet.

With these qualifications in mind, it is important to examine the robustness of finding no preference heterogeneity in sea urchin diving location choice. Two additional 50-diver random samples are drawn and Models A–D are estimated on each. The qualitative results are the same and the parameter magnitudes are comparable. For each data set, we reject the restriction of Model B to D ($\chi^2(3) = 114.55$ and $\chi^2(3) = 75.78$) but fail to reject the restriction of Model A to C ($\chi^2(3) = 5.12$ and $\chi^2(3) = 0.11$). So at first blush, it does not appear that the spurious preference heterogeneity finding is an artifact of the particular sample. The issue of model specification is explored next.

Before expanding the dimension of the random parameter vector, models are estimated with the same number of parameters but using a different parametric assumption. Since we expect that higher revenues positively influence a choice and larger distances will negatively influence a choice, it is sensible to consider a distribution that restricts the signs of parameters. Multivariate lognormal, such that $\ln(\boldsymbol{\beta}) \sim MVN(\boldsymbol{\mu}, \boldsymbol{\Omega})$, can readily implement these sign restrictions. This distribution can be estimated with simulation and has the same number of parameters as the multivariate normal. The simulated maximum likelihood routine estimates the parameters μ_{ER} and μ_{DIST} as well as the Cholesky factors in $\boldsymbol{\Omega}$. Table A1 (available online as a supplement to the paper through the website http://www.aere.org/journal/index.html) reports the raw parameter estimates for Models E and F that are log-normal versions of Models A and B. State dependence is clearly important in the model. The parameters β_{SD} and α are strongly significant and similar in magnitude to those in Models A and D. The likelihood ratio tests are consistent with those in the multivariate normal random parameters models. When state dependence is included, we fail to reject restricting parameters to having degenerate distributions. However, when state dependence is excluded, we reject restricting the random parameters. We also fail to reject restricting the initial conditions to zero ($\chi^2(11) = 14.28$).

Table 3 compares the structural parameters on ER and DIST across Models A–F. It reports the mean parameter of interest, the standard error on the mean due to sampling error, the standard error associated with heterogeneity (restricted to zero for Models B and D), and the corresponding standard error on the standard error due to sampling error. For the lognormal models, the mean of ER is $\exp(\mu_{\mathrm{ER}} + \sigma^2_{\mathrm{ER}}/2)$, and the standard error is $\sqrt{\exp(2\mu_{\mathrm{ER}})\exp(\sigma^2_{\mathrm{ER}})[\exp(\sigma^2_{\mathrm{ER}}) - 1]}$. The same transformations are used to obtain mean and standard error for DIST. The standard errors due to sampling (in parentheses under each parameter) are computed using the delta method. The standard errors attributable to heterogeneity are much larger in magnitude for Models B and F, the ones that exclude state dependence. This suggests, consistent with the likelihood ratio tests above, that random parameters in Model B and F are explaining some variation in choice that is attributable to the omitted state dependence.

For Models A, C, and E, Table A2 (available online as a supplement to the paper through the website http://www.aere.org/journal/index.html) contains the logistic transformed state dependence initial conditions, i.e. $\tilde{x}^{\mathrm{SD}}_{ij1}$ for $j = 0, \ldots, 10$, along with standard errors computed using the delta method. It compares these estimates to the empirical probability distribution of patch visits, i.e. the sample shares of activity for each patch. The initial conditions in Models A, C, and E are

Table 3
Structural parameters and heterogeneity in Models A–F

Parameter	Model A	Model B	Model C	Model D	Model E	Model F
Mean ER	0.0169 (0.0086)	0.0605 (0.0090)	0.0163 (0.0082)	0.0271 (0.0069)	0.0167 (0.0105)	0.0528 (0.0406)
Standard Error ER	0.00007 (0.00038)	0.00218 (0.00083)			0.00529 (0.0067)	0.04481 (0.0192)
Mean DIST	−7.91 (0.2482)	−13.80 (0.3827)	−7.89 (0.2223)	−11.93 (0.2385)	−7.90 (0.2243)	−14.07 (0.4306)
Standard Error DIST	0.14 (0.6453)	11.88 (1.8816)			0.28 (0.6798)	4.36 (6.1490)

Note: Standard errors from sampling error are in parentheses.

virtually identical. However, they do not exactly track the average probabilities of visiting different locations. For instance, patch 9 has a high initial condition but a small patch share. This again points to the importance of the dynamics of location choice. The empirical probabilities report average behavior over time, while the initial conditions affect behavior at the beginning of each diver's sequence. The mismatch between average behavior and behavior at the beginning of the sequence reflects an underlying dynamic process. Nevertheless, the correlations at the end of the table indicate that initial conditions are positively related to frequency of visitation.

Table A3 (available online as a supplement to the paper through the website http://www.aere.org/journal/index.html) computes marginal rates of substitution in three different ways to capture the tradeoff between distance traveled and ER. The distance-revenue tradeoff is essential to understanding how responsive commercial fishing vessels would be to a spatially explicit policy such as an area closure. While not directly comparable to a recreation demand study, a similar ratio would be involved in assessing the welfare change from an environmental quality change. In a recreation study with a simple RUM formulation, the welfare change from a marginal environmental quality change would be the ratio of the marginal utility of the site quality to the marginal utility of income. Thus, the extent to which random parameters discrete choice models accurately track marginal rates of substitution has implications for non-market valuation.

The first method simply evaluates the ratio at the means of the parameters. The second method uses Monte Carlo simulation with 1,000,000 random draws to integrate over the range of the random parameters and the range of sampling error in the models. The third method also uses Monte Carlo simulation with 1,000,000 random draws but assumes that there is no sampling error. One problem with this analysis is that the support for the multivariate normal models includes zero, so mean MRSs could be sensitive to draws near zero. To deal with this problem, Table A3 also reports median MRS and a standard deviation based on truncating the upper and lower 2.5% of the distribution. Not surprisingly, the models in which random parameters are not significant have enormous standard deviations even after the truncation. Comparing across models, the MRSs are smaller in magnitude in models that exclude state dependence (Model B compared to Model A, Model D compared to Model C, and Model F compared to Model E). Although the true MRS is not known, there appears to be a systematic dampening effect when state dependence is excluded.

4.2. Random effects and heterogeneity in state dependence

While the results in Models A–F are provocative, it is worth considering other random parameter specifications. With these data, there are only two other general types to consider: (1) random effects and (2) a random parameter on state dependence. Random effects in a multinomial model with eleven choices impose considerable computational burden, but they are important to explore because they are another potential source of temporally persistent unobservables that could be spuriously picked up by modeling state dependence. In this empirical setting, random effects could capture individual preference for unobserved geographical or oceanographic features of the patches such as embayments, wind breaks, and currents. Random effects could also capture a heterogeneous information effect if there is variation in divers' temporally persistent knowledge of good fishing areas. However, if this knowledge decays in any way or is a function of direct experience in the area, we would expect the state dependence variables to capture this type of information effect. Only diagonal elements of the random effects covariance matrix are estimated to reduce some of the computational burden.

A handful of authors have explored heterogeneity in state dependence in other discrete choice settings by interacting state dependence terms with other covariates [8], estimating correlation in state dependence across product categories [31], estimating individual-level regressions [12], and by estimating a random parameter on state dependence [3]. These studies find that heterogeneity in state dependence is important in repeated choice settings. As such, some of what we find in the previous models could be an artifact of assuming homogenous responsiveness to state dependence. By including a random parameter on state dependence and random effects with no off-diagonal covariances, and returning to the assumption that the random parameter vector is distributed multivariate normal, there are 16 unique Cholesky factors to estimate in the full model.

Table A4 (available online as a supplement to the paper through the website http://www.aere.org/journal/index.html) reports results for four different models: Model G includes fixed state dependence with random effects and random parameters on ER and DIST; Model H excludes state dependence altogether but includes random effects and random parameters on ER and DIST; Model I restricts the random effects to zero but includes random parameters on SD, ER, and DIST; and Model J is the full model. The state dependence initial conditions are all restricted to zero.[11] These results reiterate the importance of state dependence; the restriction of Model G to H is strongly rejected. Heterogeneity in state dependence appears to be important as well, since Model I cannot be restricted to Model C. Inclusion of random effects substantially increases the magnitude of the mean coefficients on ER and DIST. However, unlike in Models A–F, we do not find the result of spurious preference heterogeneity. That is, we reject restricting H to D, but we also reject restricting G to C. With Models I and J, it is not possible to perform the same tests that compare models with heterogeneity to models without when state dependence is included or excluded; by estimating the model with parameter heterogeneity, state dependence is necessarily included.

Table 4 further explores the heterogeneity in Models G–J.[12] The standard errors on state dependence are statistically significant, suggesting that heterogeneity in responsiveness to state dependence is important in the model. Perhaps more importantly, the standard errors on ER and DIST in Model H, which excluded state dependence altogether, are more than twice those of any other model. This suggests that excluding state dependence amplifies apparent preference heterogeneity.

[11] This assumption is made because models with random state dependence and initial conditions would not converge. This assumption is potentially a limitation of the analysis, but since all previous models failed to reject this restriction, the assumption seems innocuous.

[12] Note that for random effects, the standard errors that capture heterogeneity are simply the absolute values of the Cholesky factors in Table A4, and the standard errors on these standard errors are the same as the Table A4 Cholesky factor standard errors in parentheses.

Table 4
Structural Parameters and Heterogeneity in Models G–J

Parameter	Model G	Model H	Model I	Model J
Mean ER	0.0301 (0.0118)	0.1513 (0.0178)	0.0222 (0.01)	0.0325 (0.0114)
Standard Error ER	0.0395 (0.0128)	0.0984 (0.0145)	0.0234 (0.011)	0.0439 (0.0114)
Mean DIST	−11.17 (0.5908)	−23.07 (1.1814)	−8.68 (0.2814)	−10.55 (0.4639)
Standard Error DIST	1.92 (0.4498)	7.19 (0.5451)	2.73 (0.4653)	3.32 (0.2794)
Mean SD	3.916 (0.2147)		2.882 (0.0915)	3.643 (0.157)
Standard Error SD			1.899 (0.4777)	1.839 (0.3950)

Note: Standard errors from sampling error are in parentheses.

5. Discussion

It is difficult to overstate the extent of enthusiasm in marine science for managing fisheries with spatially explicit tools, including marine reserves. This enthusiasm generates a need to understand the impacts of this potentially major change in fisheries policy, and a critical driving force will be the behavioral responses of fishermen. Thus, understanding fishing location choice is essential. This paper contributes to this understanding by adapting and estimating a parameterization of state dependence originally proposed in the marketing literature. This reduced-form model for the influence of past choices on future ones has substantial explanatory power and provides a significant improvement over previous discrete fishing location choice models. This paper is also the first in fisheries economics to estimate a discrete choice model with more than one random parameter.

In the presence of location choice state dependence, short- and long-run behavioral responses of the fishing fleet will differ. As in any dynamic econometric model with positive autocorrelation in the dependent variable, the instantaneous effect of a change in one of the independent variables is amplified in the long-run. The larger this autocorrelation is, the greater difference there will be in short- and long-run effects. This may provide some explanation for why the magnitudes of the structural coefficients (on ER and DIST) appear larger when state dependence is excluded from the model but heterogeneity is included. The difference between short- and long-run effects of a change in ER vary across the sample of divers because the different histories of divers lead to different values of the state dependence covariates. Temporally persistent unobservables as modeled by random parameters on ER and DIST effectively proxy for this heterogeneous dynamic adjustment process.

Although the full bioeconomic implications are not yet well understood, simple models of sluggish adjustment in entry and exit decisions suggest how state dependence will matter. In bioeconomic models of entry and exit, the economic speed of adjustment can determine whether a fish stock persists in the long run as well as the extent to which fishing effort and fish stocks cycle about a steady-state equilibrium [37,42]. Since location choice state dependence is a form of sluggish adjustment, the harvest sector will respond relatively slowly to increases or decreases in the fish stock. This behavior potentially leads to bioeconomic cycling at the level of fishing grounds and not just in the aggregate fishery. Whether spatial sluggishness of the harvest sector would generate net benefits or losses is unclear. Consider a marine reserve that increases the biomass in a fishing location through spillovers from the reserve. With sluggish adjustment, the benefits to the fishery will take longer to materialize, which one would expect to reduce the net present value of the policy due to the effect of discounting. On the other hand, with sluggish adjustment under open access, the benefits will take longer to dissipate, thus increasing the net present value of the policy.

Future research on fisheries should be able to implement the techniques described in this paper. It is no surprise that many of the existing empirical analyses of state dependence and heterogeneity use supermarket scanner data, which are ideally suited to this type of analysis. This paper demonstrates that commercial fishing logbooks are also ideally suited to dynamic discrete choice modeling. Though the sea urchin data set may seem uncharacteristically rich, fishing vessels are often and increasingly required to report these types of data in logbooks. As regulators move to implement spatially explicit management tools, the requirement for spatial detail will likely increase. Moreover, use of GPS technology can generate dynamic and spatial data that is more reliable and on a finer scale than self-reported data. Thus, the ability to estimate complex econometric models of fishing decisions will only continue to grow.

On a deeper level, the empirical results in this paper support a finding of true state dependence and some preference heterogeneity. These particular results caution more against modeling preference heterogeneity in isolation than against modeling state dependence in isolation. When making location choices, it may not be that individual harvesters differ, per se, but that they have had very different experiences exploiting the resource and thus have different expectations about the spatial character of the resource. This is a particularly likely scenario in fishing or any other search activity in which individuals learn about opportunities by recording their own successes, observing the successes of others, and accumulating knowledge by actually choosing areas and sampling opportunities. In such a setting, each individual operates over a different information set, and choices observed reflect not so much the actual data observed by the econometrician, but unobservable processing of that data by individuals in the sample. An important caveat is that some other form of unobserved heterogeneity is temporally autocorrelated and thus appears as true state dependence. Though one could invoke this caveat in any econometric model that involves repeated decisions, the importance of state dependence persists even with a parameterization that includes patch-specific random effects. Perhaps a more important caveat is simply to acknowledge that with so many potentially important structural determinants of dynamic behavior, there could be a specification error in the state dependence model itself. Moreover, spatial autocorrelation could be picked up by state dependence if it is not reflected in spatial variation in ER or travel distances.

The problem of discrete location choice is fairly generic and one that has strong relevance for resource and environmental economics. For recreation demand in particular, the choice structure is often very similar to the one studied in this paper. Thus, these results suggest caution in interpreting random parameters in recreation demand models if researchers are unable to model state dependence. McFadden and Train show that the Mixed Logit is capable of approximating "any discrete choice model derived from RUM" (p. 995) [24]. This is an important consideration because it does not necessarily mean that random parameters represent the true structure of the data generating process, but instead that they approximate it well. This appears to be at least part of the reason that random parameters were found to be significant in Model B when state dependence was not modeled but not in Model A that included state dependence. Nevertheless, the more elaborate parameterizations of preference heterogeneity in Models G and H temper this finding. Excluding state dependence may magnify the apparent preference heterogeneity that is in the model but not necessarily generate preference heterogeneity where none exists.

The sensitivity of results to whether state dependence is included or excluded, to some extent, is the converse of the problem that Heckman explored in 1981 [15], where the emphasis was on the emergence of spurious state dependence when heterogeneity is not modeled properly. Thus, further research is needed both in evaluating the performance of Mixed Logit when there is a dynamic data generating process and in applying these tools to other data sets covering a variety of location choices. Moreover, further research is warranted to examine the structural determinants of state dependence in repeated location choice. In the long run, it is also important to gather and analyze diary-type data to understand the location choice problem. While both random parameters and state dependence impose computational burdens in discrete choice models, as computing power continues to grow, collecting the requisite data may pose even bigger challenges in the future.

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