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Analysis

Economic spillovers in spatial harvest behavior

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A B S T R A C T

There has been a strong push within natural resource management to incorporate spatial structure into management regimes. However, discussions surrounding the appropriate designs of spatial management have largely been conceptual. This paper develops a spatial econometric model of fishing location choice using non-confidential data from the Great Barrier Reef coral trout commercial fishery. Harvest location decisions are modeled as a function of spatial patterns of expected economic returns. The preferred spatially dependent econometric model is shown to outperform ordinary least squares and fixed effects models in out-of-sample forecasting. Estimates from the spatial model reveal spatial spillover effects in fleet harvest location behavior. In particular, harvest activity at any given site is equally sensitive to same-site economic returns and surrounding-site economic returns. The econometric results are illustrated using a fee-based policy simulation. Results suggest non-spatial management is characterized by two inefficiencies. First, heterogeneity between sites is averaged, resulting a fee that is too high or too low across space. Second, fees that are too high or too low affect the fishing effort in nearby locations.

1. Introduction

Recent scientific advancement in geographic information systems and remote sensing have transformed the way spatial patterns in social-environmental systems are understood. Many biophysical systems were once viewed as being homogeneous over their entire geographic range, yet researchers are more recently uncovering important spatial heterogeneities in economic processes governing these systems (Wilen, 2004; Brozović et al., 2010).

Economists posit that resource returns can be improved by apportioning spatial distributions of economic activity in ways which reflect underlying spatial heterogeneities (Sanchirico and Wilen, 2005; Rassweiler et al., 2012). Options for spatial management range from the spatially blunt, such as marine protected areas, to the spatially complex, such as zonal-based fee programs. Nevertheless, while stylized conceptual analyses suggest there are gains in moving from non-spatial management to spatial management, the magnitude of such gains will depend on empirical and contextual factors. For instance, one might suppose that if there is considerable spatial variation in harvester behavior then the gains from spatial management will be large. Yet, the amount of spatial variation in behavior is fundamentally an empirical question. Additionally, how might spatial economic spillovers affect the gains to spatial management? Using empirical evidence to explore the subtleties of spatial economic linkages is important to policy because it will arguably be costlier to enforce spatially detailed regulations and policy makers can use such information to estimate cost-recovery. Indeed, models of spatial behavior are increasingly being used to inform the design of spatial regulations, so better understanding of fleet behavior is likely to improve policy outcomes directly (Wilen, 2004; Rassweiler et al., 2014).

The focus of this paper is to test for spatial economic spillovers in fleet responses to spatial patterns of expected economic returns. Economic spillovers are defined here as the average change in fishing effort at a focal site in response to changes in expected economic returns in nearby sites. A sizeable empirical literature has investigated implications of spatial closures (Curtis and Hicks, 2000; Smith and Wilen, 2003; Hicks et al., 2004) but studies devoted to behavioral response of harvesters to more nuanced spatial regulations are relatively few (e.g Hicks and Schnier, 2010). Spatial heterogeneity and spatial correlation are posited to be important in the determination of spatial behavior (Hicks and Schnier, 2010; Schnier and Felthoven, 2011), yet few studies explicitly account for these factors. In addition, new spatial management paradigms (e.g. zonal fees) are by construction intended to produce spatially heterogeneous patterns of economic incentives (Antle et al., 2003; Parker, 2007; Muller and Mendelsohn, 2009), which are likely to further enhance spatial interactions (i.e. management in one area influences harvest in surrounding areas) (Sanchirico and Wilen, 2001; Smith and Wilen, 2003; Costello and Polasky, 2008).

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Empirical analysis of spatial behavior and spatial policies is complicated by different challenges. Spatial data are oftentimes positively correlated over space, such that locations that are near one another are more related than locations that are distant (Tobler, 1970). Identification of interaction effects across spatial entities is made difficult by these natural spatial correlations, which can either reinforce or attenuate spatial interactions. Moreover, if interaction effects are present and spatial autocorrelation is unobserved, then empirical estimation will be inaccurate (Irwin and Bockstael, 2002). Spatial econometric models offer means to control for spatial autocorrelation by incorporating spatial interactions (Anselin, 1988). Another common limitation to spatial analyses is difficulty in obtaining detailed observer or logbook data. For instance, in the US spatial harvest data meets the definition of trade secrets as defined in the US Freedom of Information Act (5 U.S.C. 552) and Trade Secrets Act (18 U.S.C. 1905). Under these circumstances, data are only released to the public if they meet specific aggregation mandates. To demonstrate, in an article in *ScienceMag*, Ray Hilborn of the University of Washington states "I would love to get my hands on it [observer data] for some of the fisheries I work on, but most jurisdictions prohibit releasing information on fishing vessels unless it is aggregated into more than three vessels (Stokstad, 2012)." While aggregated (i.e. non-confidential) spatial data are available to researchers and practitioners worldwide, they present challenges to empirical analysis when sites are censored for not meeting the aggregation mandates.

This paper empirically estimates harvest location choice as a function of spatial patterns of expected harvest returns using 10 years of publicly available spatial economic data from the Great Barrier Reef (GBR) Marine Park commercial coral trout fishery. I obtain industry-level month and 30 nautical mile site-level data from Queensland Department of Agriculture, Fisheries, and Forestry (QDAFF). The key explanatory variable in the empirical model (expected revenues from harvest) is potentially correlated with the error term because of spatial spillovers and positive spatial autocorrelation in catch rates and biological productivity (Bode et al., 2016). I employ an unconstrained Spatial Durbin Model (SDM) which controls for this endogeneity. The SDM is shown to outperform ordinary least squares and fixed effects models in out-of-sample forecasting. Using SDM, I find that approximately half the site-level elasticity of harvest effort with respect to expected economic returns can be attributed to patterns from surrounding sites, suggesting fleet behavior is governed by nuanced spatial interactions. Using the econometric estimates and an illustrative fee-based policy simulation, it is shown that non-spatial management suffers from two inefficiencies. First, heterogeneity in economic conditions between sites is averaged away, resulting in a fee that is too high in some sites and too low in others. Second, fees that are too high at any given site affect fishing effort at nearby sites through spillovers.

Considerable attention has been applied to models explaining how fish stocks change over space and time. However, in many cases ecological models of spatial population dynamics assume spatial harvest effort to be exogenously pre-determined (Wilen et al., 2002). This paper does not couple metapopulation dynamics to the economic model, but contributes to the literature by illustrating an approach to exploit widely available non-confidential data and tests for the type of nuanced spatial interactions in harvest behavior that is central to designing and evaluating new frontiers of spatial management.

This paper is structured as follows. Section 2 provides background to the GBR commercial coral trout fishery. Description of the data and empirical strategy are presented in Sections 3 and 4. Presentation and discussion of the empirical results follows in Section 5. A policy simulation is presented in Section 6. The paper concludes with a summary discussion and outlook on further research.

2. The GBR marine park commercial coral trout fishery

The GBR contains approximately 3000 individual reefs and is the world's largest reef system. A lot of the value in the GBR commercial fin fish fishery derives from sale of live coral trout (*Plectropomus leopardus*), which fetch ex vessel prices of AU$30–50/kg and annual gross value product of AU$25–30 million (Thébaud et al., 2014).[1] Commercial fishing accounts for three-quarters of all coral trout catch (Department of Agriculture Fisheries and Forestry, 2013). Management of the commercial coral trout fishery falls under the jurisdiction of QDAFF.

Prior to financial year 2004–2005, the commercial coral trout fishery was managed via limited entry (beginning in 1983), gear restrictions, and area closures amounting to 5% of the total GBR Marine Park area.[2] In July 2004, per the *Great Barrier Reef Marine Park Zoning Plan 2003*, the total area of the Marine Park closed to fishing increased from 5% to 33%.[3] Additionally, a total allowable commercial catch (TACC) of 1288 annual metric tons was introduced for coral trout based on historic catch levels (Department of Agriculture Fisheries and Forestry, 2013). Recent landings have been below the TACC, which is attributed to severe cyclone activity and the expansion of no-take zones (Table A1).[4]

3. Data

The fishery data used in this analysis was collected by QDAFF and includes monthly-aggregated observations on effort spent fishing for coral trout and landings of coral trout for the 2004–2005 through 2013–2014 financial years within the GBR Marine Park. Each observation provides fishing location at 30 nautical mile spatial resolution. In total there are 71 different spatial units and 120 months. Observations where fewer than 5 licenses were active in a given site in a given time period (e.g. month, year) are censored from the dataset by the regulator. Fig. 1 and Table A2 summarize the spatial distribution of effort within the GBR aggregated over the 2004–2005 through 2013–2014 financial years. The most heavily fished sites are generally located close to port (Fig. 1). Spatially aggregated data across the GBR Marine Park at the month-level and spatially disaggregated data at the financial year-level were also obtained (Tables A1 and A3).

For this study, sites where fewer than 5 licensed vessels were active in a financial year (thus not appearing in the financial year-level dataset) are considered inactive sites and are imputed zeros for catch and effort for each month in that financial year.[5] There are a total of 1547 site-month observations in the dataset that are imputed zeros for this reason. Sites where 5 or more licenses were active in a financial year, yet are censored from the month-level dataset are considered active sites.[6] Monthly values for these sites are imputed using Predictive Mean Matching (PMM) (Little, 1988), which is discussed in greater detail below. Within the dataset, there are 8520 total possible site-month observations. Of this total, 3056 are observed directly from QDAFF, 1547 are considered inactive and are imputed zeros, and 3917 are considered active yet censored and are imputed using PMM.

As part of an auxiliary dataset, I obtained occurrences of tropical cyclones off the coast of Queensland between 2004 and 2014 from the Bureau of Meteorology (Table A4). I also obtained monthly averaged retail diesel prices at the Queensland regional level and monthly average unemployment at the state level (Table A5). Hourly wave data

[1] It is estimated that 85–90% of commercial coral trout landings are live product. Dead product sells at approximately half the value of live product.

[2] The financial year in Australia starts on July 1 and ends on June 30.

[3] See Thébaud et al. (2014) for further background on management of the GBR.

[4] Despite the TACC being non-binding, quota lease exchanges have maintained positive prices (Thébaud et al., 2014) due to the quota having option-like characteristics (Newell et al., 2005) and the potential for the fishery to provide inframarginal rents to some fishermen (Johnson and Libecap, 1982).

[5] For context, the average number of annual vessels active in a given site from 2004–2005 through 2013–2014 is 17.

[6] In other words, it is known that a site was fished by 5 or more licenses from the end of year annual reporting, but the specific month(s) during which fishing occurred is unknown from the data and therefore require imputation.