The Economics of Marine Conservation.*

Robin Burgess	Jonathan Colmer	Michael Greenstone
LSE	University of Virginia	University of Chicago

Preliminary and Incomplete – Please Do Not Cite or Distribute

Abstract

The privatization of common-pool resources, through conservation areas, has long been argued to be an effective way of internalizing the negative externalities imposed on society, through unsustainable extraction and environmental degradation. However, whether conservation areas are effective in practice, or whether they simply result in a reallocation of extraction efforts is an open question. Using a boundary-level regression discontinuity design, and new data containing high-resolution satellite data on fishing activity and ocean health we evaluate the effectiveness of over 700 marine protected areas (MPAs) across the globe. We estimate significant reductions in fishing activity, and increases in net primary productivity (NPP) – a key measure of ecosystem services, suggesting that MPAs are indeed effective at reducing fishing effort and increasing ocean productivity within conservation areas. However, we find that fishing effort is reallocated to other fishing grounds, completely offsetting the increases in NPP realized within protected areas. Our findings suggest that the behavioral responses of regulated agents can substantially undermine the efficacy of place-based policies.

*This Version: November 2017.

Correspondence: j.colmer@virginia.edu. Affiliations: Burgess – Department of Economics, London School of Economics, UK; Colmer – Department of Economics, University of Virginia, USA; Greenstone – Department of Economics, University of Chicago, USA.

We thank Chris Costello, Steve Miller, and participants of the UCSB Occasional Workshop for helpful thoughts, comments, and discussion. We thank Scott Doney and Maria Kavenaugh for numerous conversations and advice, relating to the science of oceanography and marine biology. We thank Will Oestreich for outstanding research assistance. All errors and omissions remain our own.

1 Introduction

The relationship between economic and natural systems has long been a central focus in the natural and social sciences (Marsh, 1865; Malthus, 1798; Sen, 1981). Humanity is constantly striving to improve their welfare by pursuing economic growth, involving large increases in energy consumption and natural resource use, and in turn damages nature, and imposes negative externalities on society, through environmental degradation and unsustainable practices (Ciriacy-Wantrup, 1952; Coase, 1960; Krutilla, 1967; Harding, 1968).

In the 150 years since George Perkins Marsh's seminal 1865 book *Man and Nature*, the influence of humankind on nature has increased exponentially to a point where the living systems on which humanity depends are threatened. One of the most stark reflections of this damage is the exploitation and degradation of the global oceans. Ocean fisheries provide a critical source of food and protein, supporting a substantial fraction of the global human population, especially in parts of the developing world. However, since 1950, phytoplankton concentrations – important for generating around two-thirds of the atmosphere's oxygen, sequestering carbon, and forming the base of virtually every ocean food web –, have declined by 40% (Boyce et al., 2010). Furthermore, it is believed that over this same period commercial fishing has extracted over 90% of big-fish stocks and that today 64% of global fisheries are being exploited unsustainably, having a stock biomass that exceeds the maximum sustainable yield (Myers and Worm, 2003; Costello et al., 2012). Beyond the direct effects on fish stocks, commercial fishing activity is thought to have far-reaching ecological consequences, potentially leading to substantial degradation of the marine environment, altering food webs, and destroying critical habitats (Halpern et al., 2008).

This degradation and exploitation is largely due to the absence, or limited nature, of property rights. Naturally, this points to a role for government intervention in the form of protection and conservation. Anecdotally, much has been discussed about the role that marine protection areas can play in the context of conservation. Following World War II increases in fish stocks observed in the North Sea, when fishing grounds were inaccessible because of the presence of mine fields, motivated the first formal description of the use of closed areas as a tool for fisheries management (Beverton and Holt, 1957). As marine ecosystems became more heavily exploited over time the need to manage and protect marine environments became more salient; however, to address these concerns countries had to address the governance of marine areas. In 1958, the Geneva Conventions on the Law of the Sea provided the first international legal framework to address sovereignty and jurisdictional rights to the seabed beyond the customary 3-mile territorial sea. However, it was not until 1994 that the United Nations Convention on the Law of the Sea (UNCLOS) and the Convention

on Biological Diversity (CBD) come into force. These last two conventions greatly increased the rights of nations to implement marine protected areas. The key reason for this was the establishment of the 200 nautical mile exclusive economic zone, facilitating the establishment and management of MPAs outside a country's territorial waters. As part of the 2011 CBD 193 countries agreed to manage 10% of coastal and marine areas within marine protected areas and "other effective area-based conservation measures" by 2020 (Secretariat of the CBD, 2011). This target was also included under Goal 14 of the United Nations Sustainable Development Goals (SDGs).

However, while there has been considerable discourse, there is scarce evidence on whether such conservation efforts are effective, and if so the determinants of effective conservation. Instead it is assumed that MPAs are effective if properly regulated and actively managed. Furthermore, concerns about "paper parks" – areas that simply legislated, yet not actively managed or enforced –, raises questions about the efficacy of MPAs.

In the 1979 volume of the American Economic Review (Papers & Proceedings), Maurice Wilkinson noted,

"The shortage of empirical research largely reflects the lack of biological knowledge and data. The consequences of this situation are that policy decisions are resolved in an arena devoid of the benefit (or constraint) of estimates of the economic benefits and costs of alternative courses of action."

Since this time biological knowledge has advanced greatly, producing new theoretical insights and a vast modelling literature that has been used to assess and evaluate ocean health and productivity; however, quality observational data, necessary for rigorous evaluation of conservation efforts has lagged behind. To date the majority of evidence, exploring the effectiveness of MPAs and fisheries management has been theoretical, based on select local-scale case studies, or based on simple before/after or inside/outside comparisons of abundance (Gordon, 1954; Scott, 1955; Johnson and Libecap, 1982; Karpoff, 1987; Sanchirico and Wilen, 2005; Fisher and Laxminarayan, 2010; Pollnac et al., 2010; Stavins, 2011; Edgar et al., 2014; Halpern, 2014; Costello et al., 2015; Gill et al., 2017). This evidence has provided mixed reports on the effectiveness of MPA, largely due to the poorly defined counterfactuals, as well as the absence of a globally-representative dataset on MPAs.

We make two key contributions towards the evaluation of MPAs and conservation areas: data and methodology. Exploiting recent advances in remote-sensing technology we construct a high-resolution global dataset on fishing activity – constructed using ship-tracking (AIS) data, combined with machine-learning algorithms used to classify fishing behaviour –, and ocean productivity – exploiting satellite data on net primary production (NPP), a key

measure of ecosystem services, based on phytoplankton concentrations.[1]

We combine this data with information on the location and establishment of 711 Marine Protected Areas (MPAs), implemented globally between 1900 and 2013, and apply a boundary-level regression discontinuity design to identify the causal effects of marine protection, providing insights into the degree to which human intervention can influence ocean productivity.

We estimate that MPAs result in a reductions in fishing effort, and significant increases in NPP, suggesting that, on average, MPAs are effectively enforced, and that this translates into significant ecological and socio-economic benefits. In addition, we explore the drivers of effective conservation, finding that coastal, medium-sized, mature, locally-managed MPAs are most effective in increasing ocean productivity and reducing fishing effort. By contrast, large MPAs are not effectively enforced, and while small MPAs are enforced, they appear too small to deliver significant increases in NPP. These findings suggest that the ability to effectively monitor and enforce protected areas, as well as scale are important determinants of effective conservation.

However, even if MPAs are effective in reducing fishing effort and increasing ocean health and productivity, place-based policies may simply result in a reallocation of effort offsetting the benefits attained from conservation. Consequently, we set out to understand the aggregate consequences of MPAs. We do this by dividing the world into 500km $\times$ 500km grid cells, subtract land coverage, and explore the effects of an increase in the share of each cell that is protected on fishing effort and NPP. Interestingly, we find that an increase in protection is associated with no changes in aggregate fishing effort, but aggregate reductions in NPP, suggesting that the designation of MPAs is associated with a reallocation of fishing effort.

Our findings suggest that MPAs may be effective as a policy tool if the conservation area is focussed on protecting location-specific habitats, where reallocation of fishing effort does not offset the benefits of protection. However, where the objective is more focussed on reducing aggregate fishing effort, or improving aggregate ocean health and productivity, the behavioral responses of affected agents may substantially undermine the efficacy of MPAs, resulting in a significant misallocation of resources.

The remainder of the paper is structured as follows: section 2 provides a brief overview of the mechanisms through which MPAs may influence fishing activity and ocean productivity; section 3 describes the structure of the data used in our analysis; section 4 presents our empirical strategy; section 5 presents our results; section 8 concludes.

[1]Phytoplankton generate about half of global biomass, around two-thirds of the oxygen we breathe, and form the base of virtually every ocean food web. They also harbor much of the biodiversity on earth.

2 Mechanisms

2.1 How might Marine Protected Areas affect Fishing Activity?

While MPAs may not preclude fishing entirely, one should expect that, if monitoring and enforcement is effective that the designation of a MPA should reduce fishing effort. However, in practice this may not be the case. Concerns about "paper parks" – areas that simply legislated, yet not actively managed or enforced –, raises questions about the efficacy of MPAs. Furthermore, even if MPAs are actively managed, monitoring and enforcement is costly and so some MPAs may be more difficult to enforce than others, limiting the degree to which fishing effort is curtailed, even in areas where it is strictly prohibited.

2.2 How might Marine Protected Areas affect Ocean Productivity?

Understanding how MPAs might affect Ocean productivity, is a more complex question. The channels through which our measure of ocean productivity – NPP – can be affected are relatively clear. NPP can be affected through light, temperature, or nutrients (see appendix A for a deeper discussion. However, less clear, given their passive nature, are the mechanisms through which MPAs could affect these factors.

The most salient consideration is that MPAs may reduce overfishing, or extraction, which could have an effect on NPP, down the food chain. However, marine ecosystems have long been characterised as being bottom-up controlled. That is, while increases in NPP at the base of the food web, may affect higher trophic levels, the degree to which extraction above has impacts that trickle down to lower levels, is less clear. The degree to which food webs are affected by top-down forces (predation) remains one of the fundamental questions in ecology.

Suggestive evidence on the role that top-down forces may play has been characterized by a declining trend in phytoplankton over time. Boyce et al. (2010) report a 40 per cent drop in phytoplankton since 1950. These declines are correlated with rising sea surface temperatures; however, the authors are not able to disentangle "climate change" from overfishing. This raises an interesting question over whether human intervention in the marine biosphere can mitigate this trend. The answer to this question may also help to shed light on the importance of overfishing, compared to climate change, in driving the decline in NPP. If the decline is driven by climate change then MPAs shouldn't do much. If the decline is due to overfishing then MPAs could play a significant and important role. Alongside the decline in phytoplankton since 1950, it is also reported that over 90% of big-fish stocks have been extracted since 1950, i.e., only 10% of all large fish, including open ocean (tuna, swordfish,

etc.) and groundfish (cod, halibut, flounder, etc.) remain (Myers and Worm, 2003).

If top-down control is important, then as more fish are extracted, the amount of zooplankton (microscopic animals that eat phytoplankton, and are eaten by fish) increase, leading to a decline in phytoplankton and a reduction in biomass, resulting in trophic decline. Of course the impact on NPP depends on the trophic level, of which fish are extracted. If fish that eat zooplankton (predators) are removed then this would reduce phytoplankton. However, if fish that eat zooplankton-eating fish are removed (carnivores) then this could result in an increase in phytoplankton, and a corresponding reduction in biomass up the food chain. Figure 1 provides a graphical representation of these potential outcomes.

75% of the fish that are extracted in the oceans are forage fish, that eat zooplankton, suggesting that on average we would expect increases in zooplankton and consequently declines in NPP. An additional consideration is whether NPP will be affected even in the event of trophic decline. This depends on the degree to which extraction results in a "trophic cascade", whereby trophic levels beyond the level of extraction and the trophic level below are affected, i.e., if fish that eat zookplankton are extracted this may affect zookplankton, but may not translate into reductions in NPP. By combining data on fishing effort with data on NPP, we are able to explore the degree to which MPAs reduce fishing activity, and whether this translates into impacts on NPP, shedding light on the relevance of "trophic cascades", as well as the relevance of top-down control.

Another potential channel, through which extraction may affect NPP is through nutrient availability. The nitrogen, and other nutrients, that phytoplankton require for photosynthesis comes in part from the decomposition of fish carcasses and fish excrement (Nicol et al., 2010). Consequently, when fish are extracted there are fewer dying fish and less fish excrement, reducing the nutrients available for phytoplankton, reducing NPP. Therefore, if MPAs reduce overfishing this may increase the nutrients available for phytoplankton, increasing NPP.

A final consideration, unrelated to extraction, is that MPAs may reduce traffic and pollution in the area, reducing turbulence and pollution, increasing the penetration of sunlight at the surface. Pollution may also have a direct effect on phytoplankton, affecting biomass. To the degree that these channels are relevant MPAs should be positively associated with an increase in NPP, if enforced.

3 Data

3.1 Fishing Activity Data

Fishing activity data comes from the Global Fishing Watch, a collaboration between Oceana, SkyTruth and Google, which set out to provide real time information on commercial fishing. The data is produced, starting with raw Automatic Identification System (AIS) data, which contains both positional and identity information for vessels. The AIS is an automatic tracking system used for maritime safety. Vessels broadcast their location to navigate and to avoid collisions with other ships, providing a unique vessel ID, country of origin, the speed travelled, and the course. These signals are recorded by satellites and terrestrial receivers. Between 2012 and 2016 Global Fishing Watch has recorded over 24 billion signals, from over 250 thousand vessels, around 60,000 of which are known, or likely, to be commercial fishing boats. The database is expanding with over 22 million data points being added to the system every day.

Fishing vessels are identified by matching the raw data to fishing registries. Where this data isn't available fishing vessels are classified using a neural net model to predict vessel and fishing gear types, e.g. long liners, trawlers, etc. Vessel tracks are then used to determine when fishing is happening and when a boat is moving to a new location, using a logistic regression model trained, using 240,000 hours of hand-labeled AIS data conducted by fishing experts and the use of ship logbooks.

The final data product contains around 60,000 likely fishing vessels, providing daily measures of fishing activity, on a $0.1^\circ \times 0.1^\circ$ grid, from 2012 and the present (it really is real time). Figure 2 illustrates the spatial variation in the average number of hours per day that fishing occurs between 2012 and 2015.

Fishing tracks are available for trawlers, drifting longliners, purse seiners, fixed gear, jiggers, and other types. We focus on trawlers, drifting longliners, and purse seiners, as detection accuracies are highest for these types: 83% for Trawlers and Longliners, and 97% for Purse Seiners (de Souza et al., 2016)

Fishing trawlers operate by actively dragging a fishing net along the bottom, or through the water column at a specified depth. While trawling, vessels usually slow down and aim to maintain a constant speed to keep the strain on dragged nets as even as possible. Trawling speeds are usually characterized by slow, steady speeds between 2.5 and 5.5 knots (de Souza et al., 2016).

Longliners operate using a long line with baited hooks attacked at intervals, and are commonly used to catch swordfish and tuna, as well as many other species. Hundreds, or even thousands, of baited hooks can hang from a single longline (up to 100km in length).

When a line is set the vessel travels only slightly slower than full speed. Afterwards, the line is left in the water for a period of hours, before the vessel reverses and returns along the line. Consequently, Longliners are characterized by spatial-temporal movement patterns in a very restricted area (de Souza et al., 2016).

Purse Seines operate through the use of long nets that are deployed vertically from floats around schooling fish. To avoid fish escaping, the setting of the seine has to occur quickly and is done at high speeds. Once the net encircles the school completely the bottom of the net is pulled shut (like a purse), stopping the fish from swimming down to escape the net.

Figure 3 presents examples of fishing tracks for each of these vessel types. Dots represent individual AIS detection signals, lines represent interpolated tracks.

These three types of vessel account for over 86% of all "recorded" fishing activity in the data; however, it is likely that fishing activity is misattributed for these other vessels. Consequently, trawlers, drifting longliners, and purse seiners likely account for more than 86% of "true" fishing activity in the data. Using this data we define our outcome variable to be the average number of fishing hours per day for each year.

3.2 NPP Data

While numerous methods have been developed to estimate primary production, the spatial variability provided by satellite methods provides the most promising approach to estimate NPP for econometric research. Alternative approaches, known as "Incubation Methods" measure the properties of discrete water samples, representing a square meter of ocean. Over the past 20 years only 80 integrated Carbon-based PP estimates are available annually for the world's oceans (Chavez et al., 2011). By contrast, a single global 9-km resolution satellite image contains over 4 million data points (pixels), the great majority of which have never been sampled in-situ. Due to the limitations of incubation methods significant efforts have been made in deriving algorithms to estimate NPP from satellite ocean color estimates of near-surface chlorophyll. Alternative sources of data that have been used to evaluate ocean productivity include stock assessments, such as those from the RAM Legacy Stock Assessment Database (Ricard et al., 2011; Costello et al., 2012; Heal and Rising, 2014). However, although these assessments provide a longer annual time series the spatial variation is very limited, with only 336 regions across the globe. As discussed, each satellite image contains over 4 million regions, providing variation not only within assessment regions, but also within MPAs.

The data we use on NPP comes from the Oregon State Ocean Productivity Project, which applies Vertically Generalized Production Models (VPGM) to satellite data. The standard

VGPM is a "chlorophyll-based" model, based on (Behrenfeld and Falkowski, 1997), that estimates NPP from chlorophyll, using an empirical relationship between chlorophyll and the photosynthetic carbon-uptake rate per unit of chlorophyll. This is adjusted for sea surface temperature and integrated over the euphotic zone using sunlight intensity and day length.

The satellite data is drawn from MODIS chlorophyll and temperature data, SeaWiFS photosynthetically active radiation (PAR), and estimates of euphotic zone depth from a model developed by Morel and Barthon (1989), based on chlorophyll concentration. We use monthly data between 2003 and 2015, available at a resolution of $0.08° \times 0.08°$. We then calculate annual average NPP to account for seasonal variation in the thermocline.

Despite the significant advantages that remote sensing data provides, there are two obvious concerns associated with satellite data in this context. First, satellite-based methods are less accurate than incubation methods, especially close to shore, where suspended nonliving colored materials can bias estimates. However, this should not be too much of a problem in our context given that most of the analysis will be local, i.e., "just within" vs. "just outside" the boundary of MPAs. Second, satellite algorithms are applied over weekly or monthly composite data, to reduce the effects of clouds and other errors, reducing the variability of NPP, compared to incubation data. However, spatial variability is of greater importance than short-run temporal variability in our context.

Figure 4 presents the spatial variation in NPP between 2003 and 2015, our sample period.

3.3 Marine Protected Areas

Data on Marine Protected Areas comes from the World Database on Protected Areas. The raw data contains 14,215 MPAs. After removing non-designated MPAs, those that do not report a year of designation, and non-IUCN categorised MPAs we are left with a sample of 7,118 MPAs that were implemented between 1874 and 2013. After combining these data with the NPP data we are left with a final analysis sample of 753 MPAs. This is largely due to the resolution of the NPP data. While there are over 4 million cells per frame of data, many MPAs are too small to analyse as we require at least one data point both within and outside of the MPA. The average reported marine area in the full sample is 3,125 km^2, with over 60% of MPAs reporting a marine area smaller the resolution of the NPP data. Consequently, it is important to highlight that we are under-representing small MPAs. Later analysis will explore the degree to which scale may be an important contributor to effective marine protection, which will shed some light as to whether the estimates we provide are likely to be under or over-estimates for the full sample of MPAs. However, it is important

to note that while we only have 10% of the total number of MPAs, we capture 80% of the total area covered by MPAs in the full sample.

Figure 5 presents the number of MPAs in the analysis sample over time. 98% of these MPAs were implemented post-1958 (red line), following the Geneva Conventions on the Law of the Seas, and 63% were implemented post-1994 (blue line), following the introduction of the United Nations Convention on the Law of the Sea (UNCLOS) and the Convention on Biological Diversity (CBD).

These MPAs are under the management of 74 countries; however, 50% are located in 7 countries (Australia, USA, Indonesia, Russia, Norway, New Zealand, and Canada).[2] Figure 6 presents the spatial location of the 711 MPAs in our sample.

Table 2 presents summary statistics for the final analysis sample. In addition to size and year of establishment characteristics, we observe that 44% of MPAs are coastal, and that $\approx$ 90% are managed by government. The remaining 10% are split between jointly-managed MPAs ($\approx$ 8%) and locally-managed MPAs ($\approx$ 2%). Finally, it is important to note that while 73% of the sample contain no take zones, many of the MPAs in the database do not report no take status, resulting in only 186 MPAs with data, relating to this characteristic.

Comparing the analysis sample to the full sample of MPAs, we observe that we are undersampling MPAs that are small, coastal, and locally managed. We are also oversampling younger MPAs. This is consistent with the fact that more recently the trend has been to form large MPAs in waters far from the coast. In 2016 the title of "largest MPA" changed twice, from the U.S. Papahanaumokuakea Marine National Monument, to the Ross Sea Protected Area in Antarctica. Understanding the differences between the full sample of MPAs and our analysis sample will help us to shed light on the degree to which our sample estimates of MPA effectiveness are or underestimates of the population treatment effect.

4 Empirical Strategy

One of the main concerns associated with the evaluation of protected areas is the endogenous placement of conservation sites, that is non-protected areas do not provide a suitable counterfactual to infer outcomes in the absence of MPAs.

However, the boundaries of Marine Protected Areas provide us the opportunity to identify the causal effects of marine conservation. While the location and characteristics (such as size) of MPAs are endogenous, the boundary lines of MPAs are plausibly exogenous. While decision-makes may decide the size and location of an MPA, the exact location of boundaries are unlikely to be endogenous outcomes. Furthermore, due to the absence of straight lines

[2] 30% are located in Australia, USA, and Indonesia.

in nature, it is also unlikely that other factors correlate strongly with the location of MPA boundaries. This allows us to use a regression discontinuity design to identify the causal effects of Marine Protection on ocean health and fishing activity.[3] Due to the large number of MPAs and observations our approach we include boundary fixed effects, consistent with other geographic or boundary RDD studies (Black, 1999; Dell, 2010; Casaburi et al., 2013).

The identification problem can be described using the potential outcomes framework. Define $y_i(1)$ as the potential outcome for cell i when the cell is protected by an MPA, and $y_i(0)$, when it is not protected. In this case the population parameter of interest is the average treatment effect, $\text{ATE} = \mathbb{E}[y_i(1) - y_i(0)]$. The identification problem is that that we cannot observe the cell in both states of existence: protected and non-protected. That is we only observe the realized outcome, based on the protection status of the cell T_i:

$$y_i = T_i \cdot y_i(1) + (1 - T_i) \cdot y_i(0)$$

OLS estimation will lead to an inconsistent estimate of the ATE in the presence of unobservable covariates that are correlated with both the outcome and the protection status of the cell. As discussed, even with multiple rounds of data, a difference-in-difference estimator is still likely to be biased due to the endogenous selection of sites for marine protection.[4] By contrast, our RDD approach relies on comparisons of cells "just within" and "just outside" the boundary of the MPA. The empirical strategy identifies the average treatment effect around the cutoff. Consequently, the ATE is local such that the results around the treatment effect at the cutoff, and so the usual caveat applies that our results cannot be generalized to other points away from the cutoff.[5]

We define D_{ijk} as the distance between each cell, i, and the boundary, j of its closest MPA, k. We then estimate a local-linear regression of the form:

$$y_{ijkt} = \alpha + \beta_1 T_{ijk} + \gamma_L (1 - T_{ijk}) \cdot D_{ijk} + \gamma_R T_{ijk} \cdot D_{ijk} + \delta_{jk} + \lambda_{kt} + \varepsilon_{ijkt}$$

where y_{ijkt} is our measure of ocean productivity, net primary production, or the number

[3] See Imbens and Lemieux (2008) and Lee and Lemieux (2010) for an extensive review of the RDD literature and methodology.

[4] Furthermore, for many MPAs pre-designation data doesn't exist, and for those that have pre-designation we cannot guarantee that this data is not "treated" due to the way that the status year is coded. We focus on post-designation data. Prior to being designated boundaries are proposed. We do not know the proposal date of MPAs. Furthermore, the status year on designated MPAs may relate to date of designation or date of implementation. Again, we cannot differentiate. Consequently, any pre-implementation data we have may be confounded by announcement effects or post-designation effects. That is, we know that post-designation data is treated, but we are unsure whether pre-designation data is untreated.

[5] Although, to the degree that we find effects at the boundary of an MPA, it is likely that such effects should remain, and may even increase towards the center of MPAs.

of hours per day spent fishing in cell i, closest to boundary k, of MPA k, in year t. T_{ijk} is equal to 1 if cell i is within MPA k, and 0 otherwise. We focus on post-designation data, due to the limited number of pre-designation observations. That is we subtract the year of observational data from the year of designation, $t - \tau$, and focus on observations where this measures if greater than or equal to zero. In addition, we include boundary fixed effects, δ_{jk} and MPA-year fixed effects λ_{kt}. In addition to local-linear regressions we test the robustness of the results to polynomial approximations of D_{ijk} up to the fourth-order and varying bandwidth restrictions. Initial bandwidth choices are selected following Calonico et al. (2014) and implemented using software provided by Calonico et al. (2017). Standard errors are clustered at the MPA level.

5 Main Results

We begin by exploring the effects of marine conservation on Fishing Activity and NPP – our measure of ocean productivity.

The degree to which MPAs are able to effectively impact the ecosystems that they are trying to conserve, ultimately depends on the degree to which these areas are effectively monitored and enforced. To explore this consideration we begin by exploiting data on fishing activity, drawn from AIS ship tracking data between 2012 and 2015 (discussed in section 3). The outcome variable of interest is the average daily number of hours of fishing activity within each cell over the course of the year.

In figure 7, using an unrestricted sample of NPP and fishing activity data, we show that there is a positive correlation between NPP and fishing in the cross-section, i.e., higher NPP cells are associated with higher levels of fishing activity. This provides support for the premise that higher levels of NPP are associated with higher fishing potential, consistent with the bottom-up control, generally considered to characterise marine ecosystems.

However, in figure 8, we show that within each cell, an increase in fishing activity is associated with a reduction in NPP the following year, suggesting that top-down forces, associated with extraction, may be important, and transition through to the primary producer level – a trophic cascade. Consequently, to the degree that MPAs are enforced, reducing fishing activity within the protected area is likely to result in an increase in NPP, on average.

With these correlations in hand, we explore the degree to which the designation of MPAs affects fishing activity, using the empirical strategy described above.

Table 3, explores the effects of MPAs on fishing activity. We estimate that the designation of an MPA is associated with a reduction in fishing activity, suggesting that, on average, MPAs are enforced. Our findings are robust to different polynomial approximations for

distance (columns 2-4) as well as to different bandwidth restrictions (figure 10).

In light of this evidence it is interesting to also explore the consequences of marine protection on NPP – our measure of ocean productivity, and important metric for ecosystem services.

In Table 4, we present findings that suggest that the designation of a MPA is associated with an increase in NPP around the boundary. Again our findings are broadly robust to different polynomial approximations for distance (columns 2-4) as well as different bandwidth restrictions (figure 12).

In addition, to our main findings we also explore whether there are any other differences around the boundary of MPAs that could confound our results. While there are a limited number of confounding factors that could play a role, the first-order concern is bathymetry – ocean depth. Importantly, we find no evidence of boundary discontinuities in the bathymetry data (Table 5).

6 Exploring Heterogeneity

While we find robust evidence that the designation of MPAs are associated with increases in NPP and reductions in fishing effort, it is likely that there exists substantial heterogeneity in the degree to which MPAs are enforced, and consequently, the effectiveness of marine protection.

This section explores heterogeneity in the effectiveness of MPAs along several margins that we deem may be important for enforcement. First, we explore heterogeneity between coastal and oceanic MPAs. Second, we explore heterogeneity in the size of MPAs. Third, we explore heterogeneity based on whether an MPA has a no-take zone. Fourth, we explore heterogeneity in the governance of MPAs. Finally, we explore heterogeneity in the maturity of MPAs.

6.1 Coastal vs. Marine

We begin by exploring the degree to which there may exist heterogeneity in the effectiveness of MPAs between coastal and non-coastal MPAs. A priori, one might expect that coastal MPAs are easier to monitor and enforce (lower variable cost), due to their proximity to land. Consequently, to the degree that enforcement is an important driver of MPA effectiveness we may expect Coastal MPAs to experience more significant reductions in fishing effort and increases in NPP following designation. The results of this exercise are presented in Tables 6 and 7.

Exploring the differential effects of coastal vs. non-coastal MPAs on fishing effort, we observe that coastal MPAs experience significant reductions in fishing activity at the boundary following designation. By contrast, non-coastal MPAs do not experience any change in fishing effort.

Turning to NPP, we estimate relative increases in NPP for coastal MPAs, compared to non-coastal MPAs. Non-coastal MPAs also experience small increases in NPP. Collectively, these results provide suggestive evidence that coastal MPAs are more effectively enforced than non-coastal MPAs.

6.2 Size

Secondly, we explore the degree to which the size of an MPA is a moderating factor in driving the effectiveness of marine protection. A priori, it is unclear whether larger or smaller MPAs are likely to be more effective. On the one hand smaller MPAs are easier to monitor and enforce (lower variable cost). At the same time, given the mobility of fish MPAs may only be effective once they become sizeable enough to offer effective protection (economies of scale). Furthermore, if scale is important for effective marine protection the benefits of protection may only exceed the costs for larger sites (lower average fixed cost). I split the the marine area of MPAs into terciles: small (< 192 km^2); medium (192 - 1,437 km^2); large ($> 1{,}437$ km^2). The results of this exercise are presented in Tables 8 and 9.

We observe that following the designation of an MPA there are significant reductions in fishing activity in medium-sized MPAs, and an almost complete reduction in fishing activity in small MPAs, relative to the control mean, consistent with the premise that smaller MPAs are easier to enforce. However, we observe no reductions in fishing effort for larger MPAs, consistent with the premise that large MPAs are more difficult to enforce.

Expanding to the full sample, we observe again that medium-sized MPAs are associated with significant expansions in NPP, as well as relative reductions in NPP for large MPAs, suggesting again that larger MPAs may be more difficult to enforce. In addition, we also observe that small MPAs also experience relative reductions in NPP, resulting in insignificant absolute effects, despite the effective enforcement of small MPAs, suggesting that scale may be an important factor for effective conservation.

6.3 No Take Areas

Third, we explore whether the effectiveness of MPAs is moderated based on whether all or part of the MPA is assigned as a no-take area. A priori, one might expect that no take areas are more strictly monitored and enforced and have a greater potential for conservation.

However, the endogenous selection of MPAs as no-take areas may highlight the returns to extraction. Consequently, the degree to which no-take areas are enforced will be an important determinant of whether or not such sites are effective at conservation. The results of this exercise are presented in Tables 10 and 11.

Exploring the moderating effects of no take zones on fishing effort we observe relative reductions in the hours spent fishing in no take zones, following the designation of MPAs; however, these effects are not statistically significant. This suggests, that even MPAs that don't have no take zones can still be effective in reducing fishing effort; however, it is important to note that a significant share of the total sample of MPAs fail to report their no-take status. Consequently, the absence of statistically significant effects may relate to power considerations. Exploring the moderating effects of no take zones on NPP, we again observe no moderating effect.

6.4 Governance

Fourth, we explore the degree to which governance types may moderate the effectiveness of MPAs. I define three types of governance: government controlled, defined as an MPA governed by national or sub-national branches of government); joint governance, defined as a collaborative, joint governance structure, or government-delegated MPA; locally controlled, defined as an MPA governed by local communities, individual landowners, NGOs, Indigenous peoples. The results of this exercise are presented in Tables 12 and 13.

A priori, there is no clear champion. Government controlled MPAs may benefit from greater resources; however, attention and resources are likely allocated over a larger number of MPAs, diminishing monitoring and enforcement efforts. By contrast, locally managed MPAs likely have access to fewer resources, but monitoring and enforcement is likely to be more effective. Joint management efforts may benefit from greater access to resources and monitoring and enforcement; however, shared responsibility may diminish the effectiveness of conservation due to the potential for free-riding.

We observe that locally managed MPAs experience significant reductions in fishing activity, compared to other governance regimes, suggesting that monitoring and enforcement may be more effective in these regimes, offsetting any concerns associated with having access to fewer resources.

Exploring the effects on NPP we find results that are consistent with the effects on fishing effort, observing significant increases in the locally managed MPAs, compared to government and jointly managed projects. In addition, jointly managed projects experience relative increases in NPP, compared to government managed MPAs, suggesting gains from

monitoring and enforcement; however, these increases are not robust to cubic or quartic polynomial approximations.

6.5 Age

Finally, we seek to shed light on the dynamics of adjustment associated with our estimated increases in NPP. While it is not possible to follow MPAs over extended periods of time, it is possible to compare similar MPAs at different stages of maturity. The results of this exercise are presented in Tables 14 and 15.

We estimate that for every additional 10 years MPAs experience a 1.9% reduction in fishing activity, suggesting that there may increasing returns to the amount of time an area is conserved. This could be due to learning on either the part of managers or users, i.e., it may take time for enforcement to become effective, or for users to learn about an area's conservation status.

For NPP, we observe that an additional 10 years of maturity is associated with an additional 0.4% increase in NPP, suggesting again that there may be increasing returns to conservation.

7 Does NPP increase in the Aggregate?

An important consideration, relating to the effectiveness of MPAs, is whether the estimated increases in NPP within the boundary are aggregate increases, or whether our estimates are affected by spillover effects outside of the MPA. The potential for spillovers is interesting in the context of conservation policies as there is the potential for two competing forces. On the one hand, the designation of a conservation zone may simply result in a reallocation of activity to outside of the area, offsetting conservation efforts (see Ferraro 2002; Oliviera et al., 2007; Meyfroidt and Lambin, 2009 for examples within the context of deforestation). In this case our estimates on the effect of MPAs on NPP may be upward biased. On the other hand, the designation of a conservation zone may result in positive spillovers, increasing productivity outside of the protected area. In this case our estimates on the effect of MPAs on NPP will be downward biased. The potential for MPAs to have ecological spillover effects on biomass outside of the protected area has been a long standing debate in the ecology literature. However, empirical evidence to date has been suggestive at most (Rowley, 1994; Willis et al., 2003; Russ and Alcala, 1996; Roberts et al., 2001; Roberts et al. 2005; Russ et al. 2004; Abseamis and Russ, 2005; Russ and Alcala, 2010).

To explore the aggregate effects of conservation we divide the ocean into 500km $\times$ 500km

grid cells, subtract land coverage, and calculate the share of each cell that is protected in each year between 2003 and 2015, using our full sample of 7,118 MPAs. This data allows us to examine the effect of increasing the share of protection, within each cell, on aggregate fishing effort and NPP, providing a net effect of conservation on fishing effort and its consequences both inside and outside of the MPA. This allows us to understand the degree to which spillovers that do not depend on distance from the MPA boundary may offset the estimated benefits associated with conservation that we have identified.

Specifically, we estimate the following model,

$$y_{it} = \beta \text{MPA SHARE}_{it-1} + \delta_i + \lambda_t + \varepsilon_{it}$$

Where y_{it} is NPP or total fishing effort in cell i in year t, MPA SHARE_{it} is the share of each cell i that became protected in the previous year $t-1$, i.e., $\frac{\text{Protected Area}_{it-1}\ (\text{km}^2)}{\text{Cell Area}_{it-1}\ (\text{km}^2)} \times 100$, δ_i is a vector of cell fixed effects, and λ_t is a vector of year fixed effects.

Table 16 presents the results of this analysis. We observe that across cells a higher share of protection is associated with lower fishing effort and higher NPP. However, within-cell an increase in the share of protection is associated with no change in aggregate fishing effort and reductions in NPP. This suggests that the designation of MPAs is associated with a reallocation of fishing effort from protected waters to unprotected waters, resulting in reductions in NPP that completely offset the gains from protection identified, in the main results.

8 Conclusion

Understanding the effectiveness of conservation efforts is of key economic, sociological, and ecological importance. However, to date data limitations have impeded efforts to effectively understand whether conservation efforts have been effective, and if so, what the determinants of effective conservation are. We take advantage of new advances in remote-sensing to construct a high-resolution satellite data on fishing activity and ocean productivity to evaluate the effectiveness and enforcement of 711 marine protected areas. Exploiting the plausibly exogenous location of MPA boundaries we use a spatial regression discontinuity design to evaluate the impact of MPAs on ocean productivity and fishing activity.

We estimate significant reductions in fishing effort and significant increases in NPP "just within" the boundary, compared to "just outside" of the MPA, suggesting that on average MPAs are effective in their enforcement and that this translates into increases in ocean productivity and health.

In addition, we explore the drivers of effective conservation, finding that more mature, coastal, medium-sized, and locally managed MPAs are far more effective in increasing NPP and reducing fishing effort. These finding suggest that both scale and the ability to enforce MPAs are important determinants of conservation.

However, to the degree that reducing aggregate fishing effort is an objective of an MPA we find evidence to suggest that fishing activity is simply reallocated from protected to unprotected areas.

Our findings imply that MPAs may be effective as a policy tool if the conservation area is focussed on protecting location-specific habitats, where reallocation of fishing effort does not offset the benefits of protection. However, where the objective is more focussed on reducing aggregate fishing effort, or improving aggregate ocean health and productivity, the behavioral responses of affected agents can substantially undermine the efficacy of MPAs, resulting in a significant misallocation of resources.

References

Behrenfeld, M. and P. Falkowski (1997): "Photosynthetic Rates Derived from Satellite-Based Chlorophyll Concentration," *Limnology and Oceanography*.

Beverton, R. and S. Holt (1957): *On the Dynamics of Exploited Fish Populations*, Springer Science.

Black, S. (1999): "Do Better Schools Matter? Parental Valuation of Elementary Education," *Quarterly Journal of Economics*.

Boyce, D., M. Lewis, and B. Worm (2010): "Global Phytoplankton Decline over the Past Century," *Nature*.

Calonico, S., M. Cattaneo, M. Farrell, and R. Titiunik (2017): "rdrobust: Software for regression-discontinuity designs," *The Stata Journal*.

Calonico, S., M. Cattaneo, and R. Titiunik (2014): "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*.

Casaburi, L., R. Glennerster, and T. Suri (2013): "Rural Roads and Intermediated Trade: Regression Discontinuity Evidence from Sierra Leone," *Mimeo*.

Chavez, F., M. Messie, and J. Pennington (2011): "Marine Primary Production in Relation to Climate Variability and Change," *Annual Review of Marine Science*.

Ciriacy-Wantrup, S. (1952): *Resource Conservation: Economics and Policies*.

Coase, R. (1960): "The Problem of Social Cost," *Journal of Law and Economics*.

Costello, C., D. Ovando, R. Hilborn, S. Gaines, O. Deschenes, and S. Lester (2012): "Status and Solutions for the World's Unassessed Fisheries," *Science*.

Costello, C., N. Querou, and A. Tomini (2015): "Partial Enclosure of the Commons," *Journal of Public Economics*.

de Souza, E., K. Boerder, S. Matwin, and B. Worm (2016): "Improving Fishing Pattern Detection from Satellite AIS Using Data Mining and Machine Learning," *PLOS ONE*, 11.

Dell, M. (2010): "The Persistent Effects of Peru's Mining Mita," *Econometrica*.

Edgar, G. J., R. D. Stuart-Smith, T. J. Willis, S. Kininmonth, S. C. Baker, S. Banks, N. S. Barrett, M. A. Becerro, A. T. F. Bernard, J. Berkhout, C. D. Buxton, S. J. Campbell, A. T. Cooper, M. Davey, S. C. Edgar, G. Forsterra, D. E. Galvan, A. J. Irigoyen, D. J. Kushner, R. Moura, P. E. Parnell, N. T. Shears, G. Soler, E. M. A. Strain, and R. J. Thomson (2014): "Global conservation outcomes depend on marine protected areas with five key features," *Nature*.

Fisher, C. and R. Laxminarayan (2010): "Managing Partially Protected Resources under Uncertainty," *Journal of Environmental Economics and Managemen*.

Gill, D. A., M. B. Mascia, G. N. Ahmadia, L. Glew, S. E. Lester, M. Barnes, I. Craigie, E. S. Darling, C. M. Free, J. Geldmann, S. Holst, O. P. Jensen, A. T. White, X. Basurto, L. Coad, R. D. Gates, G. Guannel, P. J. Mumby, H. Thomas, S. Whitmee, S. Woodley, and H. E. Fox (2017): "Capacity shortfalls hinder the performance of marine protected areas globally," *Nature*.

Gordon, H. (1954): "The Economic Theory of a Common Property Resource: The Fishery," *Journal of Political Economy*.

Halpern, B. (2014): "Conservation: Making Marine Protected Areas Work," *Nature*.

Halpern, B., S. Walbridge, K. Selkoe, C. Kappel, F. Micheli, C. D'Agrosa, J. Bruno, K. Casey, C. Ebert, H. Fox, R. Fujita, H. Heinemann, E. Lenihan, M. Madin, M. Perry, E. Selig, M. Spalding, R. Steneck, and R. Watson (2008): "A Global Map of Human Impact on Marine Ecosystems," *Science*.

Harding, G. (1968): "The Tragedy of the Commons," *Science*.

Heal, G. and J. Rising (2014): "Global Benefits of Marine Protected Areas," *Mimeo*.

Imbens, G. and T. Lemieux (2008): "Regression Discontinuity Designs: A Guide to Practice," *Journal of Econometrics*.

Johnson, R. and G. Libecap (1982): "Contracting Problems and Regulation: The Case of the Fishery," *American Economic Review*.

Karpoff, J. (1987): "Suboptimal Controls in Common Resource Management: The Case of the Fishery," *Journal of Political Economy*.

Krutilla, J. (1967): "Conservation Reconsidered," *American Economic Review*.

Lee, D. and T. Lemieux (2010): "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*.

Malthus, T. (1798): *An Essay on the Principle of Population*.

Marsh, G. (1865): *Man and Nature, physical geography as modified by human action.*, Charles Scribner.

Morel, A. and J.-F. Barthon (1989): "Surface Pigments, Algal Biomass Profiles, and Potential Production of the Euphotic Layer: Relationships Reinvestigated in View of Remote-Sensing Applications," *Limnology and Oceanography*.

Myers, R. and B. Worm (2003): "Rapid Worldwide Depletion of Predatory Fish Communities," *Nature*.

Nicol, S., A. Bowie, S. Jarman, D. Lannuzel, K. Meiners, and P. Van Der Merwe (2010): "Southern Ocean iron fertilization by baleen whales and Antarctic krill," *Fish and Fisheries*.

Pollnac, R., P. Christie, J. Cinner, T. Dalton, G. Forrester, N. Graham, and T. McClanahan (2010): "Marine Reserves as Linked Social-Ecological Systems," *Proceedings of the National Academy of Sciences*.

Ricard, D., C. Minto, O. Jensen, and J. Baum (2011): "Examining the Knowledge Base and Status of Commercially Exploited Marine Species with the RAM Legacy Stock Assessment Database," *Fish and Fisheries*.

Sanchirico, J. and J. Wilen (2005): "Optimal spatial management of renewable resources: matching policy scope to ecosystem scale," *Journal of Environmental Economics and Managemen*.

Scott, A. (1955): "The Fishery: The Objectives of Sole Ownership," *Journal of Political Economy*.

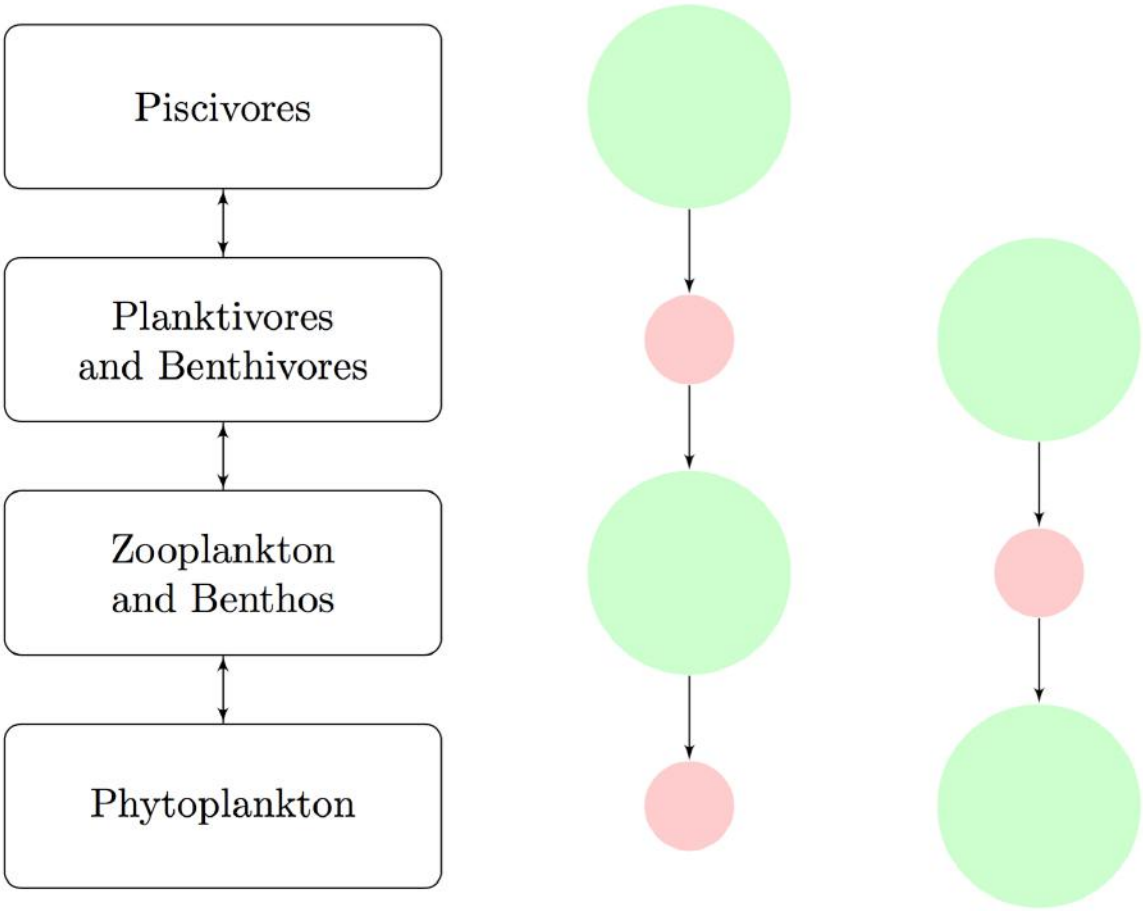
Secretariat of the CBD (2011): "Aichi Target 11. Decision X/2." *Convention on Biological Diversity*.

Sen, A. (1981): *Povery and Famines: An Essay on Entitlement and Deprivation*, Oxford University Press.

Stavins, R. (2011): "The Problem of the Commons: Still Unsettled after 100 years," *American Economic Review*.

Figures

Figure 1: A Summary of Food Web Structures



Notes: Column 1 describes the trophic levels. In this simple food chain: Piscivores eat other fish, e.g., tuna; Planktivores and Benthivores eat Zooplankton and Benthos, e.g., Anchovies and Sardines. Zooplankton and Benthos are microscopic and are not extracted. Phytoplankton form the base trophic level, i.e., they are primary producers. In columns 2 and 3, we present an illustration of how lower trophic levels could, in theory, be affected through extraction. In column 2 we illustrate how increased protection of piscivores could result in a reduction in the planktivore population – a trophic decline. To the degree that this has additional effects beyond the first trophic link, the reduction in planktivore abundance, may in turn result in an expansion of zooplankton, which in turn may reduce phytoplankton abundance – a trophic cascade (negative). Consequently, in exploring the effects of conservation on NPP, we may observe zero or positive effects in areas that target Piscivores. In column 3, we show that increased protection of Planktivores could result in a reduction in Zooplankton abundance – trophic decline. Again, if these reductions pass-through to lower trophic levels then we may observe an increase in phytoplankton abundance – a trophic cascade (positive). Consequently, in exploring the effects of conservation on NPP, we may observe negative or zero effects in areas that target Planktivores.75% of commercial fishing targets Planktivores and so, on average, we expect increased conservation to result in an increase in NPP.

Figure 2: Average Daily Fishing Hours (2012-2015)

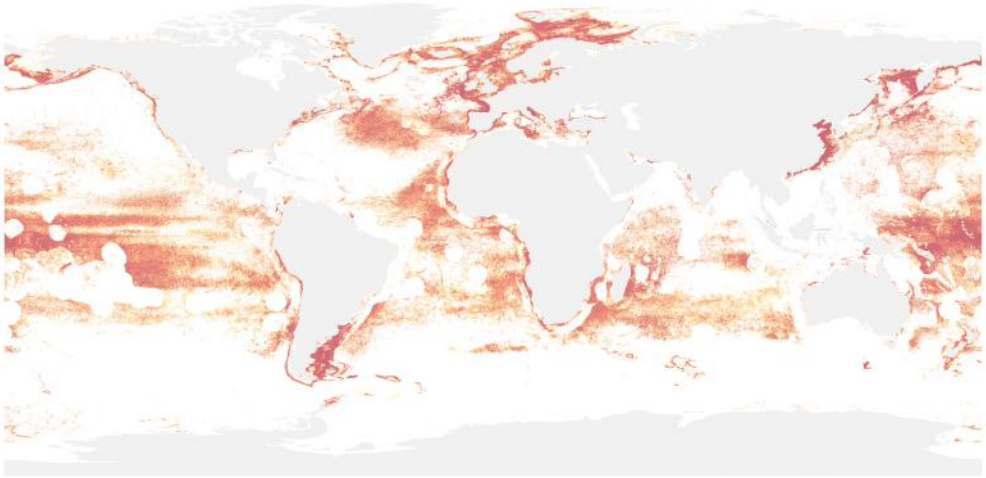
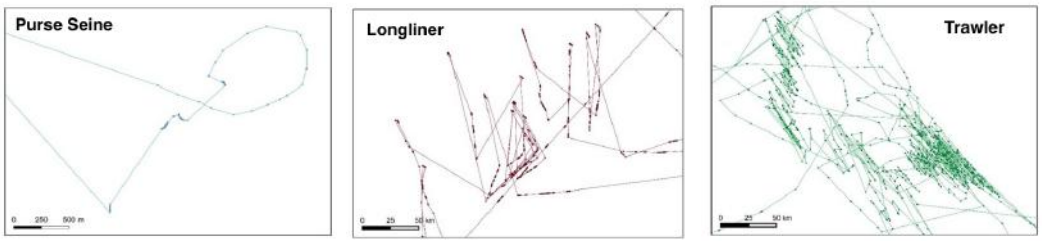


Figure 3: Raw AIS tracks for three individual vessels using different fishing gear types



Source: de Souza et al. (2016)

Figure 4: Net Primary Production (mgC/km^2/day)

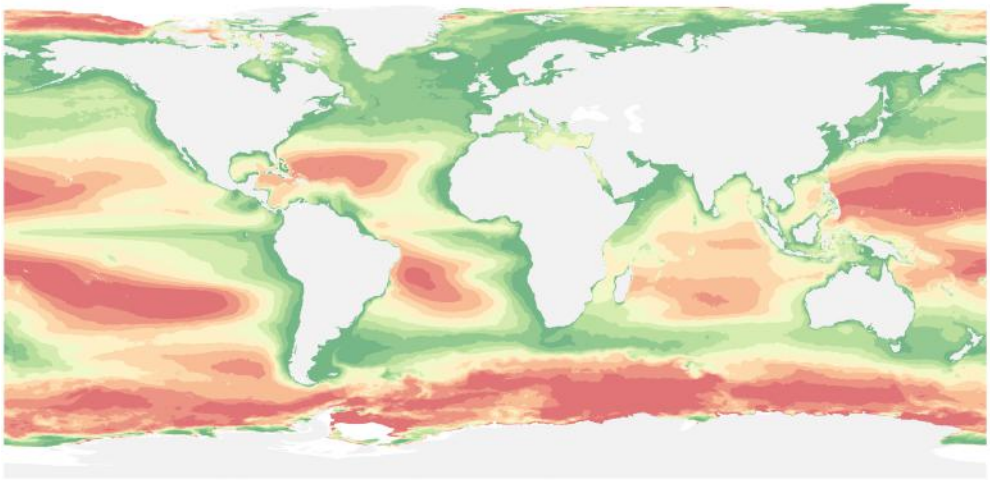


Figure 5: The Number of MPAs over Time

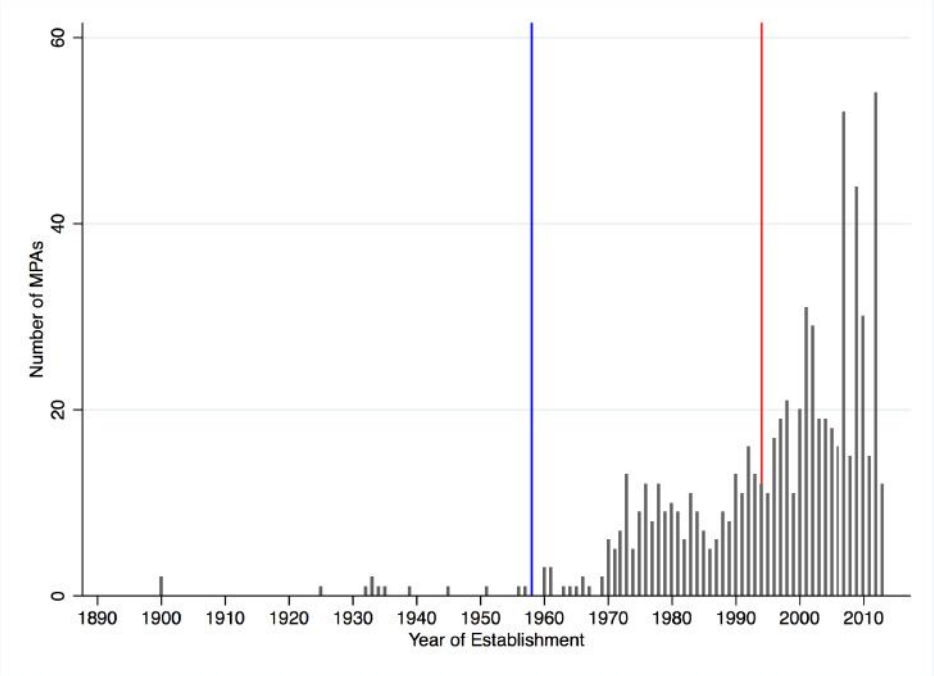


Figure 6: MPA Locations



Figure 7: The Correlation between Fishing Effort and NPP across Cells

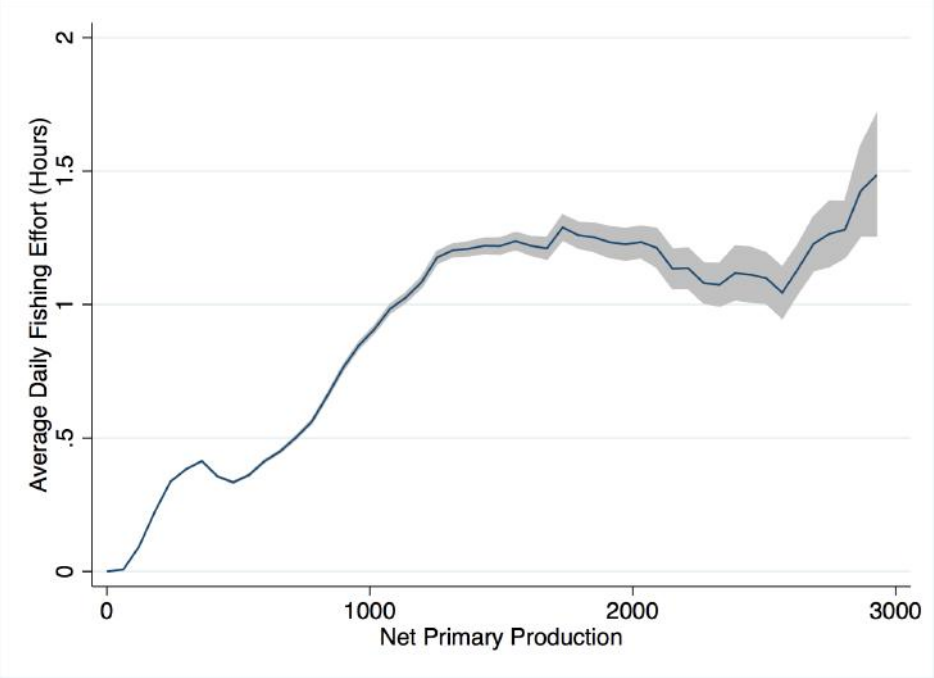


Figure 8: The Correlation between Lagged Fishing Effort on log NPP within Cell

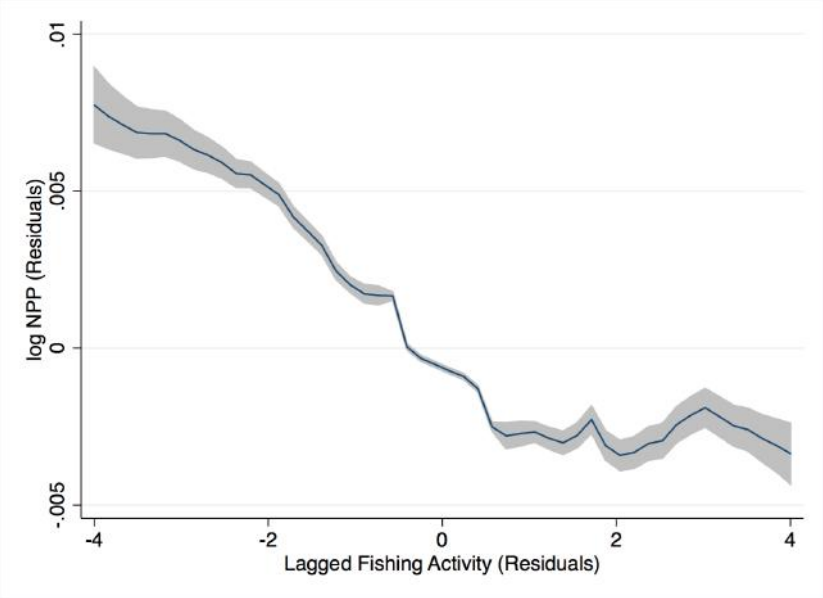
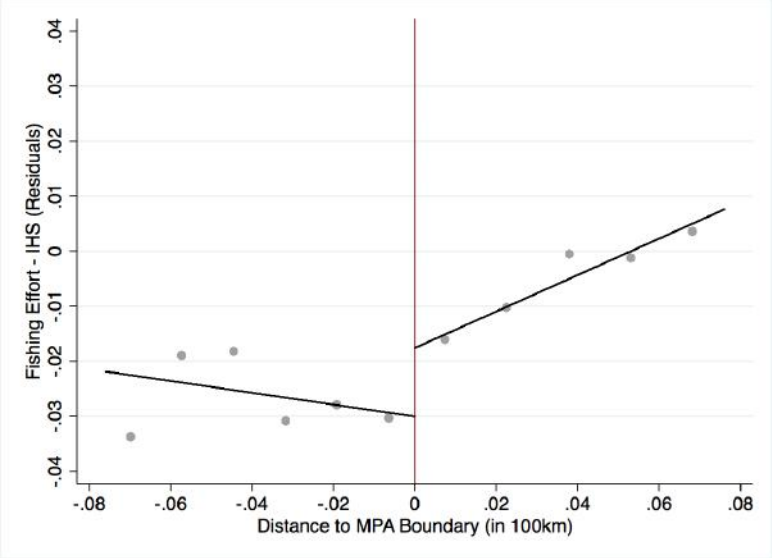


Figure 9: RDD - Fishing Effort



Notes: Each dot denotes a distance bin. The number and spacing of each bin is calculated using IMSE-optimal evenly-spaced method using polynomial regression. Results are robust to alternative methods. Positive distances denote distances outside MPAs. Negative distances denote distances within MPAs. Black lines denote a linear function of distance weighted by the number of observations in each bin. Distance bandwidths are determined following the Calonico et al. (2014) optimal bandwidth selection.

Figure 10: Bandwidth Tests – Fishing Effort

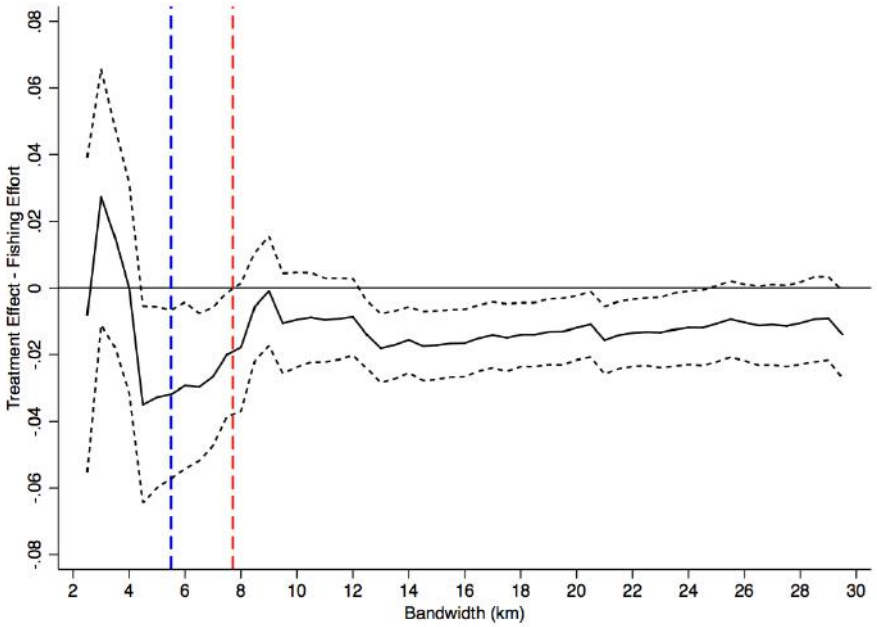
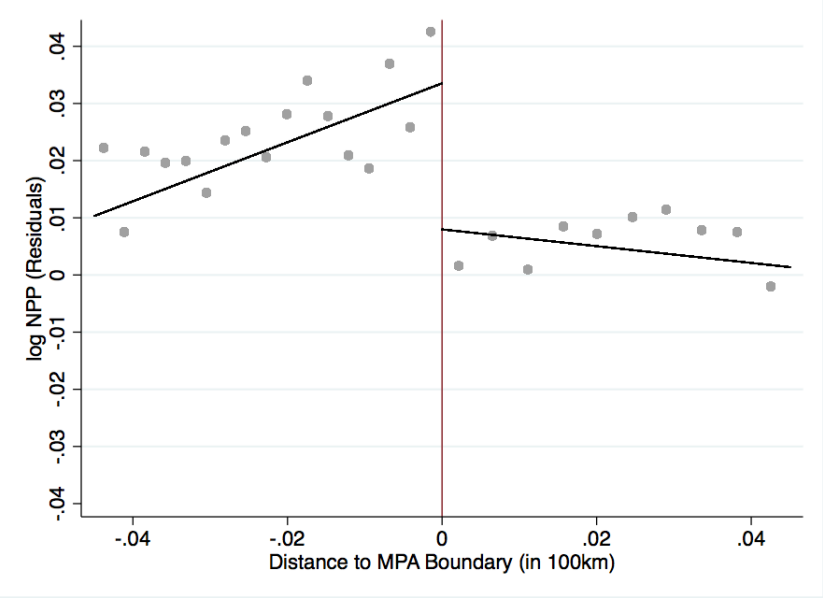
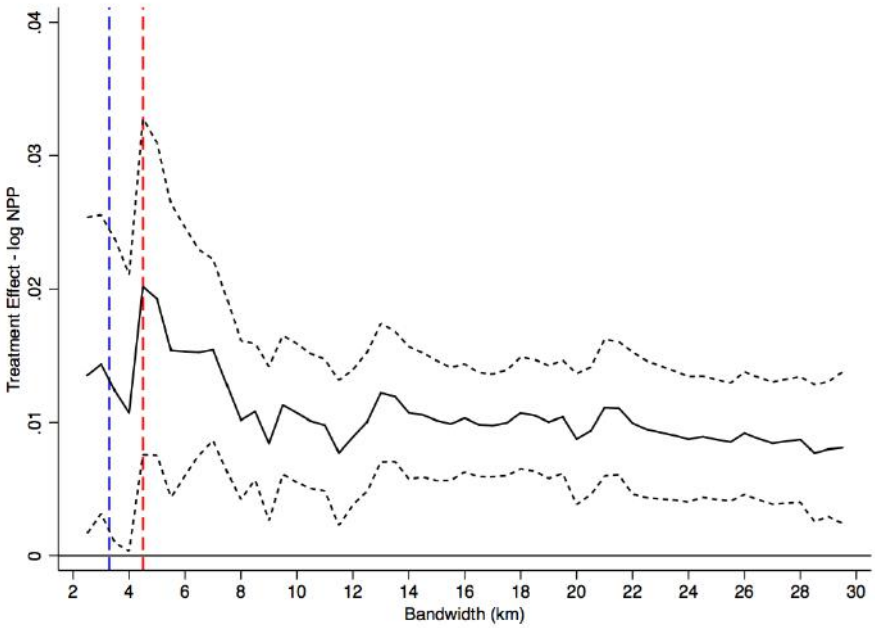


Figure 11: RDD - log NPP



Notes: Each dot denotes a distance bin. The number and spacing of each bin is calculated using IMSE-optimal evenly-spaced method using polynomial regression. Results are robust to alternative methods. Positive distances denote distances outside MPAs. Negative distances denote distances within MPAs. Black lines denote a linear function of distance weighted by the number of observations in each bin. Distance bandwidths are determined following the Calonico et al. (2014) optimal bandwidth selection.

Figure 12: Bandwidth Tests – log NPP



Tables

Table 1: Differences between Full and Analysis Sample of MPAs

	Analysis Sample Mean	Full Sample Mean	Difference
Area (km^2)	14,816.85	1,877.155	12,939.7***
	(2,649.255)	(396.680)	(3,271.183)
Year of Establishment	1995.816	1989.388	6.427***
	(0.580)	(0.232)	(0.560)
Coastal	0.443	0.662	-0.219***
	(0.018)	(0.005)	(0.017)
No Take	0.736	0.746	-0.010
	(0.032)	(0.010)	(0.031)
Government Managed	0.845	0.831	0.134
	(0.013)	(0.004)	(0.012)
Joint Managed	0.075	0.087	-0.011
	(0.009)	(0.003)	(0.009)
Locally Managed	0.014	0.043	-0.029***
	(0.004)	(0.002)	(0.004)

Table 2: Descriptive Statistics

	Mean	Median	Std. Dev.	Observations
MPA Characteristics				
Area (km^2)	19,728.05	239.64	111,937.5	534
Year of Establishment	1995	2000	15.48	711
Coastal	0.44	0	0.497	711
No Take	0.736	1	0.117	186
Government Managed	0.903	1	0.295	665
Joint Managed	0.081	0	0.273	665
Locally Managed	0.015	0	0.121	665
NPP Data				
NPP ($mgC/km^2/day$)	744.943	495.067	968.949	1,244,554
Fishing Effort				
Avg. Daily Hours	0.284	0	1.361	383,123

Table 3: Fishing Effort – All MPAs (All MPAs)

	(1) Hours/Day (IHS)	(2) Hours/Day (IHS)	(3) Hours/Day (IHS)	(4) Hours/Day (IHS)
Treat	-0.0197**	-0.0193**	-0.0202**	-0.0191*
	(0.00940)	(0.00938)	(0.0100)	(0.00995)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	115,506	115,506	115,506	115,506
Dep. Var. Mean	0.275	0.275	0.275	0.275
MPAs	696	696	696	696

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. An Inverse Hyperbolic Sine Transformation is applied to the dependent variable $\log(y + (y^2 + 1)^0.5)$. This has the same interpretation as a logarithmic transformation; however, importantly for our analysis zero is defined. Results are robust to log(y+1) transformations and estimating the effects in levels. Distance bandwidths, set at 7.6km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 4: log NPP – All MPAs (All MPAs)

	(1) log NPP	(2) log NPP	(3) log NPP	(4) log NPP
Treat	0.0202***	0.0199***	0.0106*	0.00922
	(0.00642)	(0.00631)	(0.00607)	(0.00602)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	163,618	163,618	163,618	163,618
exp(Dep. Var. Mean)	607.893	607.893	607.893	607.893
MPAs	554	554	554	554

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 4.5km, are calculated following Calonico et al. (2014). Standard errors are clustered at the MPA level.

Table 5: Bathymetry

	(1) Bathymetry	(2) Bathymetry	(3) Bathymetry	(4) Bathymetry
Treat	9.060	10.55	10.32	10.42
	(21.51)	(21.26)	(27.63)	(27.59)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
Observations Observations	12,216	12,216	12,216	12,216
Dep. Var. Mean	2,018.1	2,018.1	2,018.1	2,018.1
Clusters	726	726	726	726

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 3.7km, are calculated following the Calonico et al. (2014). Standard errors are clustered at the MPA level.

Table 6: Fishing Effort – Coastal (All MPAs)

	(1) Hours/Day (IHS)	(2) Hours/Day (IHS)	(3) Hours/Day (IHS)	(4) Hours/Day (IHS)
Treat	0.00455	0.00461	0.00439	0.00506
	(0.00929)	(0.00929)	(0.00979)	(0.00976)
Treat × Coastal	-0.0861***	-0.0855***	-0.0855***	-0.0851***
	(0.0186)	(0.0187)	(0.0187)	(0.0187)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	115,506	115,506	115,506	115,506
Dep. Var. Mean	0.275	0.275	0.275	0.275
MPAs	696	696	696	696

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. An Inverse Hyperbolic Sine Transformation is applied to the dependent variable $\log(y + (y^2 + 1)^0.5)$. This has the same interpretation as a logarithmic transformation; however, importantly for our analysis zero is defined. Results are robust to log(y+1) transformations and estimating the effects in levels. Distance bandwidths, set at 7.6km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 7: log NPP – Coastal (All MPAs)

	(1) log NPP	(2) log NPP	(3) log NPP	(4) log NPP
Treat	0.0117*	0.0116*	0.00404	0.00268
	(0.00629)	(0.00624)	(0.00672)	(0.00666)
Treat × Coastal	0.0165**	0.0164**	0.0162**	0.0161**
	(0.00649)	(0.00647)	(0.00646)	(0.00641)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	163,618	163,618	163,618	163,618
exp(Dep. Var. Mean)	607.893	607.893	607.893	607.893
MPAs	554	554	554	554

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 4.5km, are calculated following Calonico et al. (2014). Standard errors are clustered at the MPA level.

Table 8: Fishing Effort – Size (All MPAs)

	(1) Hours/Day (IHS)	(2) Hours/Day (IHS)	(3) Hours/Day (IHS)	(4) Hours/Day (IHS)
Treat	-0.0387**	-0.0383**	-0.0343**	-0.0339**
	(0.0171)	(0.0170)	(0.0171)	(0.0170)
Treat × Small	-0.0559*	-0.0543*	-0.0551*	-0.0539*
	(0.0322)	(0.0321)	(0.0320)	(0.0319)
Treat × Large	0.0334**	0.0330*	0.0331*	0.0328*
	(0.0170)	(0.0169)	(0.0170)	(0.0169)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	105,918	105,918	105,918	105,918
Dep. Var. Mean	0.232	0.232	0.232	0.232
MPAs	521	521	521	521

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. An Inverse Hyperbolic Sine Transformation is applied to the dependent variable $\log(y + (y^2 + 1)^0.5)$. This has the same interpretation as a logarithmic transformation; however, importantly for our analysis zero is defined. Results are robust to log(y+1) transformations and estimating the effects in levels. Distance bandwidths, set at 7.6km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 9: log NPP – Size (All MPAs)

	(1) log NPP	(2) log NPP	(3) log NPP	(4) log NPP
Treat	0.0330***	0.0327***	0.0289***	0.0279***
	(0.0106)	(0.0106)	(0.0106)	(0.0105)
Treat × Small	-0.0229	-0.0230	-0.0232	-0.0236
	(0.0234)	(0.0234)	(0.0234)	(0.0235)
Treat × Large	-0.0252**	-0.0250**	-0.0249**	-0.0245**
	(0.0102)	(0.0103)	(0.0102)	(0.0101)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	150,654	150,654	150,654	150,654
exp(Dep. Var. Mean)	582.308	582.308	582.308	582.308
MPAs	422	422	422	422

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 4.5km, are calculated following Calonico et al. (2014). Standard errors are clustered at the MPA level.

Table 10: Fishing Effort – No Take (All MPAs)

	(1) Hours/Day (IHS)	(2) Hours/Day (IHS)	(3) Hours/Day (IHS)	(4) Hours/Day (IHS)
Treat	-0.00590	-0.00572	-0.00199	-0.00193
	(0.00808)	(0.00806)	(0.00932)	(0.00932)
Treat × No Take	0.000851	0.000973	0.000914	0.000711
	(0.00962)	(0.00970)	(0.00971)	(0.00969)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	67,523	67,523	67,523	67,523
Dep. Var. Mean	0.101	0.101	0.101	0.101
MPAs	186	186	186	186

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. An Inverse Hyperbolic Sine Transformation is applied to the dependent variable $\log(y + (y^2 + 1)^0.5)$. This has the same interpretation as a logarithmic transformation; however, importantly for our analysis zero is defined. Results are robust to log(y+1) transformations and estimating the effects in levels. Distance bandwidths, set at 7.6km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 11: log NPP – No Take (All MPAs)

	(1) log NPP	(2) log NPP	(3) log NPP	(4) log NPP
Treat	0.0162	0.0165	0.0176*	0.0175*
	(0.0122)	(0.0123)	(0.0102)	(0.0103)
Treat × No Take	-0.00956	-0.00964	-0.00969	-0.00991
	(0.0115)	(0.0115)	(0.0114)	(0.0113)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	81,966	81,966	81,966	81,966
exp(Dep. Var. Mean)	415.299	415.299	415.299	415.299
MPAs	163	163	163	163

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 4.5km, are calculated following Calonico et al. (2014). Standard errors are clustered at the MPA level.

Table 12: Fishing Effort – Governance (All MPAs)

	(1) Hours/Day (IHS)	(2) Hours/Day (IHS)	(3) Hours/Day (IHS)	(4) Hours/Day (IHS)
Treat	-0.00927	-0.00899	-0.00771	-0.00693
	(0.00935)	(0.00935)	(0.00983)	(0.00976)
Treat × Joint	-0.00398	-0.00392	-0.00259	-0.00167
	(0.0138)	(0.0139)	(0.0146)	(0.0147)
Treat × Local	-0.0757*	-0.0731*	-0.0719*	-0.0716*
	(0.0433)	(0.0430)	(0.0431)	(0.0428)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	115,506	115,506	115,506	115,506
Dep. Var. Mean	0.275	0.275	0.275	0.275
MPAs	696	696	696	696

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. An Inverse Hyperbolic Sine Transformation is applied to the dependent variable $\log(y + (y^2 + 1)^0.5)$. This has the same interpretation as a logarithmic transformation; however, importantly for our analysis zero is defined. Results are robust to log(y+1) transformations and estimating the effects in levels. Distance bandwidths, set at 7.6km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 13: log NPP – Governance (All MPAs)

	(1) log NPP	(2) log NPP	(3) log NPP	(4) log NPP
Treat	0.0177**	0.0174**	0.0101	0.00847
	(0.00734)	(0.00721)	(0.00626)	(0.00625)
Treat × Joint	0.0271*	0.0268*	0.0189	0.0174
	(0.0161)	(0.0161)	(0.0177)	(0.0176)
Treat × Local	0.0563***	0.0559***	0.0475**	0.0455**
	(0.0179)	(0.0176)	(0.0191)	(0.0180)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	149,251	149,251	149,251	149,251
exp(Dep. Var. Mean)	614.003	614.003	614.003	614.003
MPAs	523	523	523	523

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 4.5km, are calculated following Calonico et al. (2014). NPP data for locally-managed MPAs are winsorized at the 90th percentile. Standard errors are clustered at the MPA level.

Table 14: Fishing Effort – Age (All MPAs)

	(1) Hours/Day (IHS)	(2) Hours/Day (IHS)	(3) Hours/Day (IHS)	(4) Hours/Day (IHS)
Treat	0.00464	0.00474	0.00156	0.00238
	(0.0116)	(0.0116)	(0.0120)	(0.0120)
Treat × Years	-0.00191***	-0.00189***	-0.00190***	-0.00189***
	(0.000563)	(0.000566)	(0.000565)	(0.000565)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	115,506	115,506	115,506	115,506
Dep. Var. Mean	0.275	0.275	0.275	0.275
MPAs	696	696	696	696

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. An Inverse Hyperbolic Sine Transformation is applied to the dependent variable $\log(y + (y^2 + 1)^0.5)$. This has the same interpretation as a logarithmic transformation; however, importantly for our analysis zero is defined. Results are robust to log(y+1) transformations and estimating the effects in levels. Distance bandwidths, set at 7.6km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 15: log NPP – Age (All MPAs)

	(1) log NPP	(2) log NPP	(3) log NPP	(4) log NPP
Treat	0.0140**	0.0137**	0.00453	0.00306
	(0.00694)	(0.00684)	(0.00671)	(0.00664)
Treat × Years	0.000391**	0.000390**	0.000390**	0.000392**
	(0.000194)	(0.000193)	(0.000194)	(0.000192)
Polynomial	Linear	Quadratic	Cubic	Quartic
Boundary FE	Yes	Yes	Yes	Yes
MPA-Year FE	Yes	Yes	Yes	Yes
Observations	163,618	163,618	163,618	163,618
Dep. Var. Mean	607.893	607.893	607.893	607.893
MPAs	554	554	554	554

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Distance bandwidths, set at 4.5km, are based on Calonico et al. (2014) optimal bandwidth selection. Standard errors are clustered at the MPA level.

Table 16: The Aggregate Effects of MPAs

	(1) Hours/Day (IHS)	(2) log NPP	(3) Hours/Day (IHS)	(4) log NPP
MPA SHARE (t-1)	-0.00161***	0.00587***	-0.000343	-0.000563***
	(0.00228)	(0.000814)	(0.00110)	(0.000145)
Grid FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Observations	10,723	33,984	10,723	33,984
Dep. Var. Mean	0.285	472.009	0.285	472.009
Treatment Std. Dev.	19.25	16.81	1.22	3.60

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the grid-cell level.

Online Appendices – Not for Publication

A What is NPP?

Primary Production is the process through which oxidised inorganic carbon is converted to energy-rich organic carbon molecules, through the process of photosynthesis. This process fuels essentially all life on earth, and in turn, regulates atmospheric carbon dioxide and oxygen concentrations, with significant affects on climate and biogeochemical cycles (Chavez et al., 2011).

In the oceans, photosynthesis is largely conducted by microscopic plankton that inhabit the euphotic zone – the well-lit upper few percent of the ocean. The remainder of the ocean is too dark to support net photosynthesis. Because phytoplankton live suspended in seawater amongst other non-photosynthetic organisms and particles, it is difficult to estimate phytoplankton carbon (biomass). Consequently, chlorophyll, as easily measured pigment specific to photosynthesis, has become the most widely used measure of phytoplankton abundance. Net Primary Production (NPP), the focus of our data collection efforts, is the portion of photosynthetic carbon fixation that becomes available to the non-photosynthetic components of the ecosystem, i.e., gross photosynthetic carbon fixation - phytoplankton respiration. Global marine NPP has been estimated to be around 50 petagrams of carbon per year, approximately equal to the NPP of terrestrial ecosystems (**?**).

Net Primary Production is determined by the product

$$NPP \propto F_N \cdot F_I \cdot F_T \cdot B$$

where the first three factors represent nutrient, light, and temperature limitation and B is a biomass proxy derived from phosphate and iron concentrations. For plants to thrive in oceans and lakes they need sunlight and nutrients; however, thermal stratification separates nutrients and light. Light, less dense, water floats on top of colder, less dense water. Phytoplankton are slightly heavier than water and tend to sink out of the lighted surface water, carrying nutrients with them. Stratification tends to separate nutrient rich from light rich waters.

In winter, mixing is deep and plenty of nutrients are mixed to the surface. However, phytoplankton are also circulated deeply, and due to limited light in the winter, and the ability of light to reach phytoplankton when they are mixed deeply, they are light limited. In spring, as the ocean warms, the emergence of a thermocline, reducing the depth of the mixed layer, results in an upwelling of nutrients and phytoplankton. The availability of light

and nutrients results in an increase in phytoplankton. As the summer progresses, nutrients are stripped from the water column and so primary production becomes nutrient limited. In the fall, the thermocline is eroded and winter light becomes limited, resulting in a further decline in primary production.

A.1 Why Does NPP Matter?

As discussed phytoplankton are some of the Earth's most critical organisms. They generate about half the of global biomass, around two-thirds of the oxygen we breathe, and form the base of virtually every ocean food web. They also harbor much of the biodiversity on earth.

A.1.1 Food Chains

Phytoplankton form the base trophic level, consequently an increase in primary production translates into higher trophic levels, determined by the efficiency of the food chain. The following equation maps these considerations

$$P = BE^n$$

where P = production at the highest trophic level, B = primary production, E = food chain efficiency, and n = the number of links between trophic levels. For example, if primary production in a region is 400 $\text{mgCm}^{-2}\text{d}^{-1}$ and transfer efficiency is 20%, then production at the second, third, and fourth trophic levels (n=1,2,3) would be 80, 3.2, and 0.64 $\text{mgCm}^{-2}\text{d}^{-1}$. Annual production can then be calculated by combining this with the area and duration of production. Consequently, an increase in NPP is likely to be positively correlated with production further up the food chain.

A.1.2 Carbon Sequestration

Through photosynthesis phytoplankton transform organic carbon in the atmosphere and in seawater into organic compounds. When they die they sink, carrying this carbon to the deep sea through the biological pump. This process is known as the "biological pump".

The strength of the biological pump is determined by (1) the nutrient content of the ocean, (2) the degree to which nutrients are consumed in surface waters, and (3) the carbon-to-nutrient ratio of sinking organic matter (**?**). It is calculated that if the biological pump were to stop, atmospheric CO_2 concentrations would more than double over the course of a thousand years (the time scale over which deep waters pass through the surface ocean).

Conversely, if the biological pump were to operate at full efficiency (if all ocean nutrients were used up) CO_2 concentrations would more than half current concentrations (**?**).

Consequently, if the nutrient content of the ocean or the efficiency of nutrient consumption in surface waters were improved the biological pump would become more efficient, reducing CO_2 concentrations in the atmosphere. Factors that can impede the biological pump include ocean warming, which increases ocean stratification, preventing mixing that brings up nutrients) and, more relevant in the context of Marine Protection Areas, pollution and turbulence, which can reduce the penetration of sunlight at the surface.

A.1.3 Biodiversity

Another factor that highlights the importance of NPP is the link between productivity and biodiversity. Most empirical work exploring the relationship between productivity and biodiversity suggest that the shape of the relationship is either positive or unimodal, whereby maximum diversity peaks at intermediate levels and minimum diversity bottoms out (see **?** and references within).

B Theory Appendix: Optimal Property Right Regimes in the Presence of Imperfect Enforcement

Consider a simple case in which there are two agents, denoted $i = 1, 2$, who want access to a single asset. Access to the asset, determined by the specification of property rights is captured by the variables $(\hat{x}_1, \hat{x}_2) \in \{0, 1\}$. Agent i has access to the asset if $\hat{x}_i = 1$ and does not have access if $\hat{x}_i = 0$. Private ownership gives the owner access to the asset as well as the ability to exclude all other users from access to it. In the presence of negative externalities the owner will always exercise this right of exclusion. Consequently, private ownership by agent 1 results in $(\hat{x}_1, \hat{x}_2) = (1,0)$; private ownership by agent 2 results in $(\hat{x}_1, \hat{x}_2) = (0,1)$. In the case of common ownership both agents have the right to use the asset and neither has the right to exclude the other, so $(\hat{x}_1, \hat{x}_2) = (1,1)$. If agent i has access to the asset they she can exert some effort denoted $e_i \in [0, \bar{e_i}]$ to extract value from the asset.

Given access $(\hat{x}_1, \hat{x}_2)$ and efforts (e_1, e_2), agent i's payoff is given by the following value function

$$\hat{x}_i V_i(e_i, \hat{x}_{-i} e_{-i}) - C_i(e_i)$$

where $V_i(\cdot) \geq 0$ is the gross benefit that agent i receives if she has access to the asset, and $C_i(\cdot)$ is her cost of effort, normalized so that $C_i(0) = 0$. $V_i(\cdot)$ is non-increasing in x_{-i}, reflecting the fact that when agent $-i$ has access to the asset ($\hat{x}_{-i} = 1$) their increased use may lower agent i's payoff. Note that $V_i(0, e_{-i})$ may be positive, and that this externality arises only from agent $-i$'s effort, not her access per se. For example, sustainable use of the asset ($e_i = 0$), creates no externalities, and provides a benefit, regardless of congestion effects; by contrast, unsustainable use of the asset are generated by agent's effort, and both create and are subject to congestion externalities.

Since an agent only generates an externality only if she exerts effort, there is always a (first-best) efficient outcome in which both agents have access to the asset and use it sustainably. If $V_i(0, e_{-i}) > 0$ for all e_{-i} and $i = 1, 2$ a strictly positive payoff is generated for the agent regardless of the other agent's level of effort, which implies that *all* first-best outcomes involve giving both agents access.

When benefits and costs are differentiable, efficient effort levels (e_1^*, e_2^*) satisfy,

$$\frac{\partial V_i(e_i^*, e_{-i}^*)}{\partial e_i} + \frac{\partial V_{-i}(e_{-i}^*, e_i^*)}{\partial e_i} = C_i'(e_i^*)$$

By contrast, equilibrium effort levels with common ownership (e_1°, e_2°) satisfy,

$$\frac{\partial V_i(e_i^\circ, e_{-i}^\circ)}{\partial e_i} = C_i'(e_i^\circ)$$

because the agents ignore the external effects of their actions. If $V_i(\cdot)$ is independent of e_{-i}, so that externalities are absent, the equilibrium is efficient. This would be the case if there was no congestion. But if $\frac{\partial V_{-i}(\cdot)}{\partial e_i} < 0$, then any interior equilibrium is inefficient.

In some cases, there is also a first-best outcome in which only one agent has access to the asset. This occurs if the cost of effort for one agent is very high or their benefit from exerting effort is very low. Since there are no externalities under private ownership then the first-best is achieved.

In the presence of externalities, the second-best optimal property rights allocation involves a trade-off: common ownership allows both agents to benefit from the asset, but introduces externalities, $\phi(\hat{x}_{-i}e_{-i})$, while private ownership denies the benefit to one agent but avoids externalities. Consider the case of symmetric agents where,

$$V_i(e_i, \hat{x}_{-i}e_{-i}) = \upsilon(e_i) - \phi(\hat{x}_{-i}e_{-i})$$

with $\phi(0) = 0$ and $C_i(e_i) = c(e_i)$. In this case common ownership is optimal if and only if,

$$\upsilon(e^\circ) - c(e^\circ) \geq 2\phi(e^\circ)$$

that is, if the direct benefit of granting a second agent access exceeds the externalities that this access creates.

Now consider, the case in which there is some risk of expropriation under private property $(0 \geq \gamma \geq 1)$,

$$V_i(e_i, \hat{x}_{-i}e_{-i}) = \upsilon(e_i) - \gamma\phi(\hat{x}_{-i}e_{-i})$$

In the case of perfect enforcement $\gamma = 0$ and the previous results hold. In the case of total expropriation, i.e. no enforcement $\gamma = 1$, then private property is equal to common property, and so common property will always be optimal. In the case of there being some risk of expropriation, $(0 < \gamma < 1)$ common property is optimal if the direct benefit of granting a second agent access exceeds the discounted cost that the externalities create,

$$\upsilon(e^\circ) - c(e^\circ) \geq \gamma^2 2\phi(e^\circ)$$

Consequently, in the face of expropriation risk common property is more likely to be optimal from a cost-benefit perspective. This could relate to the ability/cost of monitoring

and enforcement, i.e., if the cost of monitoring is very high, i.e., the risk of expropriation is high then common property likely dominates private property.