# Can Catch Shares Prevent Fisheries Collapse?

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**Can Catch Shares Prevent Fisheries Collapse?**
Christopher Costello, *et al.*
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**Fig. 3.** Egg and larval densities of *H. armigera* on cotton at Langfang site, Hebei Province, China, from 1998 to 2007. (**A**) Relation between egg density on Bt cotton (red circles) and non-Bt cotton (black circles) and planting year of Bt cotton. Linear model on Bt cotton (black line), $y = 185{,}476.90 - 92.42x$, $F = 69.05$, df = 1,58, $P < 0.0001$, $R^2 = 0.54$. Linear model on non-Bt cotton (red line), $y = 171{,}365.94 - 85.37x$, $F = 62.59$, df = 1,58, $P < 0.0001$, $R^2 = 0.52$. (**B**) Relation between larval density on Bt cotton (red circles) and non-Bt cotton (black circles) and survey years. Linear model on non-Bt cotton (black line), $y = 87{,}107.86 - 43.41x$, $F = 97.56$, df = 1,58, $P < 0.0001$, $R^2 = 0.63$. Data are means ± SEM. There are six samples for each point in the graphs.

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farmers. In China, a multiple cropping system consisting of soybeans, peanuts, corn, and vegetables is common. These crops also serve as hosts for *H. armigera*, and, because they do not express Bt toxin, they serve as refuges for non-resistant insects (*10*). Because cotton is not the only host crop, Bt cotton comprises about 10% of the major host crops in any province or throughout northern China. This accidental approach to refuge management appears to have, so far, warded off the evolution of resistance (*10*). Nevertheless, as a result of decreased spraying of broad-spectrum pesticides for controlling cotton bollworm in Bt cotton fields, mirids have recently become key pests of cotton in China (*18*, *19*). Therefore, despite its value, Bt cotton should be considered only one component in the overall management of insect pests in the diversified cropping systems common throughout China.

# Can Catch Shares Prevent Fisheries Collapse?

Christopher Costello,[1]* Steven D. Gaines,[2] John Lynham[3]†

Recent reports suggest that most of the world's commercial fisheries could collapse within decades. Although poor fisheries governance is often implicated, evaluation of solutions remains rare. Bioeconomic theory and case studies suggest that rights-based catch shares can provide individual incentives for sustainable harvest that is less prone to collapse. To test whether catch-share fishery reforms achieve these hypothetical benefits, we have compiled a global database of fisheries institutions and catch statistics in 11,135 fisheries from 1950 to 2003. Implementation of catch shares halts, and even reverses, the global trend toward widespread collapse. Institutional change has the potential for greatly altering the future of global fisheries.

Although the potentially harmful consequences of mismanaged fisheries were forecast over 50 years ago (*1*, *2*), evidence of global declines has only been seen quite recently. Reports show increasing human impacts (*3*) and global collapses in large predatory fishes (*4*) and other trophic levels (*5*) in all large marine ecosystems (LMEs) (*6*). It is now widely believed that these collapses are primarily the result of the mismanagement of fisheries.

One explanation for the collapse of fish stocks lies in economics: Perhaps it is economically optimal to capture fish stocks now and invest the large windfall revenues in alternative assets, rather than capturing a much smaller harvest on a regular basis. Although this remains a theoretical possibility for extremely slow-growing species

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(7), it remains rare in reality. A recent study reports that under reasonable economic parameterization, extinction is suboptimal (even with low growth rates) and that biomass under economically optimal harvest is larger than that under maximum sustainable yield (8).

If global fisheries contain large potential profits [perhaps a present value of $1 trillion (9)], yet the profits are only realized if the fisheries are managed sustainably, why are actively managed fisheries systematically overexploited? The answer lies in the misalignment of incentives. Even when management sets harvest quotas that could maximize profits, the incentives of the individual harvester are typically inconsistent with profit maximization for the fleet. Because individuals lack secure rights to part of the quota, they have a perverse motivation to "race to fish" to outcompete others. This race can lead to poor stewardship and lobbying for ever-larger harvest quotas, creating a spiral of reduced stocks, excessive harvests, and eventual collapse.

Examining specific cases, Beddington et al. (10), Hilborn et al. (11), Grafton et al. (12), and Griffith (13) argue that rights-based fisheries reforms offer promising solutions. Rather than only setting industry-wide quotas, fishermen are allocated individual rights. Referred to as catch shares or dedicated access privileges, these rights can be manifest as individual (and tradable) harvest quotas, cooperatives, or exclusive spatial harvest rights; the idea is to provide—to fishermen, communities, or cooperatives—a secure asset, which confers stewardship incentives. Most readily implemented within national jurisdictions (that is, inside 200 miles), some international agreements attempt to serve a similar function in international waters. Although both theory and

empirical evidence suggest a robust link between catch shares and economic performance of a fishery (14, 15), the link with ecological performance is more tenuous. Even so, Sanchirico and Wilen (16) argue that "It is widely believed and supported by anecdotal evidence that once fishers have a financial stake in the returns from sensible investment in sustainable practices, they are more easily convinced to make sacrifices required to rebuild and sustain fisheries at high levels of economic and biological productivity." A recent report provides examples consistent with this widely held belief (17). We tested the hypothetical causal link between the global assignment of catch shares and fisheries sustainability.

Whereas individual fishing rights have been implemented on small spatial scales in traditional cultures for millennia, the adoption rate in major fisheries has accelerated since the late 1970s. To test the efficacy of catch shares, we assembled a global database of 11,135 commercial fisheries and determined which fisheries had instituted catch shares from 1950 to 2003. We matched this institutional database to the same harvest database (18) used to assess fisheries collapse by Worm et al. (6). Our objective is to answer the question: Can catch shares prevent fisheries collapse?

In their widely cited contribution, Worm et al. (6) correlate the species richness of LMEs with fisheries collapse. They define a fishery as collapsed in year $t$ if the harvest in year $t$ is <10% of the maximum recorded harvest up to year $t$. Using this definition, ~27% of the world's fisheries were collapsed in 2003. Extrapolating this trend into the future, Worm et al. (6) find that 100% of the world's fisheries could be collapsed

by 2048. Although this highly controversial projection (19) captured most of the attention from this article, a larger focus of the work was the role of ecosystem biodiversity in preventing collapse. Fisheries in more biodiverse regions were less likely to be collapsed at any given point in history. Unfortunately, however, this greater resilience to human exploitation does not change the ultimate conclusion. Biodiversity does not prevent collapse; it merely delays it.

In our analysis, we expanded beyond the characteristics of the ecosystem to consider the characteristics of the regulating fisheries institutions, simultaneously controlling for the ecosystem, genus, and other covariates. To assemble our catch-share database, we searched the published literature and government reports, interviewed experts on global fisheries, and vetted our final database with a diverse array of researchers. In total, we identified 121 fisheries managed using catch shares—defined as variations on individual transferable quotas (ITQs)—by 2003 (20). These work by allocating a dedicated share of the scientifically determined total catch to fishermen, communities, or cooperatives. This provides a stewardship incentive; as the fishery is better managed, the value of the shares increases. By analyzing the data at the fishery level [rather than the aggregate level, as in (6)], we facilitate inclusion of fisheries institutions as independent variables in our model specification.

We adopt the Worm et al. (6) definition of collapse. Although a better measure would be based on stock (21), no systematic database of global fish biomass exists. This collapse metric may overestimate the frequency of collapsed fisheries (22), which creates a conservative test for the benefits of catch shares. Sensitivity analyses that



**Fig. 1. (A)** Percent of fisheries collapsed with (dotted line) and without (solid line) ITQ management using the Worm et al. (6) collapse threshold (10% of historical maximum). The number of ITQ fisheries increases through time (right *y* axis an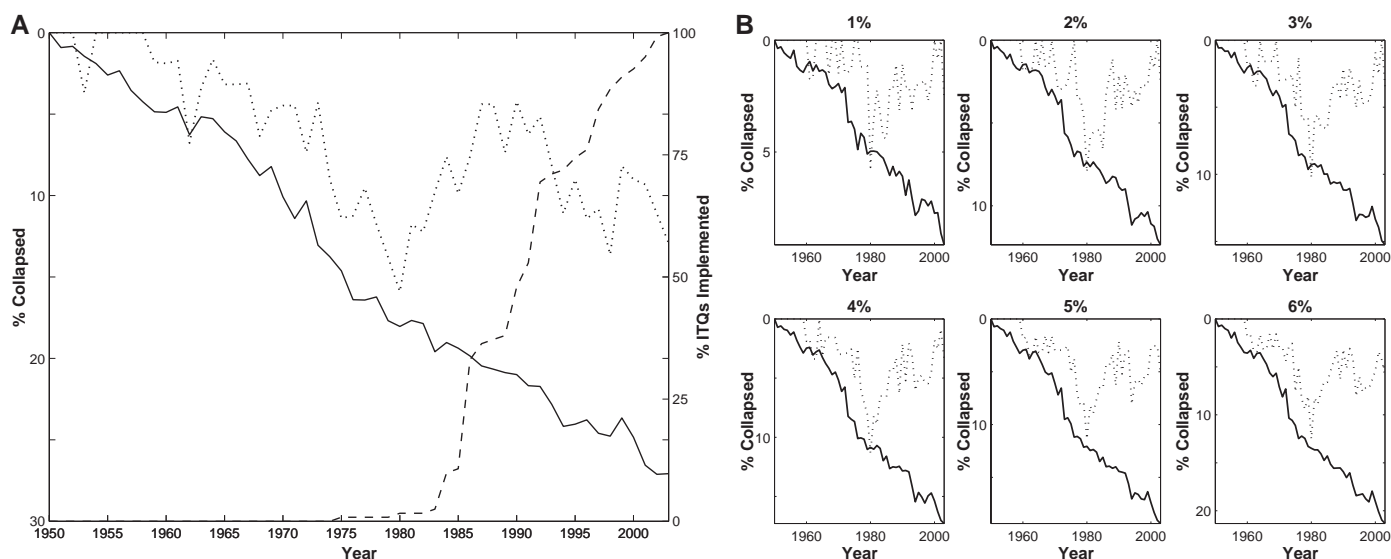d dashed line), and the rate of implementation has been accelerating. **(B)** Percent of fisheries collapsed with (dotted line) and without (solid line) ITQ management using more conservative collapse thresholds: 1 to 6% of historical maximum catch.

**Fig. 2.** Simulation of trend in fisheries collapse if all non-ITQ fisheries switched to ITQs in 1970 (dotted line), compared with the actual trend (solid line). The thought experiment assumes that the annual ITQ benefit counterbalances the global trend toward complete collapse, which is consistent with the observed trends in actual ITQs (Table 1). Fluctuations in the simulation arise from estimated interannual variability.
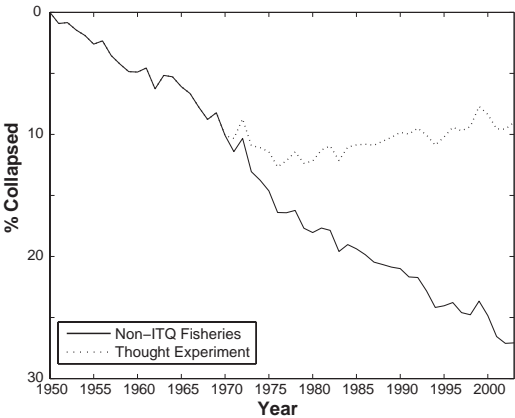


**Table 1.** Fishery-specific analyses of ITQ benefits. Each fishery is treated as a time series of collapse, with some fisheries converting to ITQ during the interval. Propensity score matching (25) controls for the effects of LME, genus, or species to further isolate biases that may arise from the particular places and fisheries where ITQs have been implemented. Columns 2 to 5 provide regression model results for four different propensity score models. Rows 2 and 3 provide the regression coefficients and SEs (in parentheses). Fisheries without ITQ management had an average annual percentage change of 0.54. For all comparisons, the annual benefit of ITQs roughly counters the current rate of decline in other fisheries (23). All estimated coefficients are statistically significant at the 1% level.

| Parameter used to match fisheries | None | LME | Genus | Species |
|---|---|---|---|---|
| Percent ITQ difference (SE) | −7.06 | −7.41 | −6.79 | −6.87 |
| | (0.49) | (0.428) | (0.443) | (0.441) |
| Annual percent ITQ effect (SE) | −0.49 | −0.37 | −0.54 | −0.51 |
| | (0.136) | (0.137) | (0.136) | (0.139) |

consider alternative thresholds for collapse and address other potential biases yield unchanged or stronger conclusions (23).

By 2003 the fraction of ITQ-managed fisheries that were collapsed (dotted line in Fig. 1A) was about half that of non-ITQ fisheries (solid line in Fig. 1A). Accelerated adoption of ITQs began in the late 1970s (dashed line and right *y* axis in Fig. 1A). In the preadoption period, would-be ITQ fisheries were on trajectories toward collapse, similar to non-ITQ fisheries. In the adoption period, the two curves diverge as ITQs are increasingly adopted (24). This disparity grows over time (23).

Demonstrating statistically a causal linkage between rights-based management and fisheries sustainability is complicated by three competing effects. First, the number of ITQ fisheries is growing, and new ITQ fisheries are drawn from a global pool with an ever-increasing fraction of collapsed fisheries. Random selection from this global pool could mask some benefits of rights-based management. Second, the conversion of fisheries to ITQs may involve a biased selection. For example, ITQs may be implemented disproportionately in fisheries that are already less collapsed, possibly giving a misleading perception of benefits from rights-based management. Finally, there may be temporal benefits of an ITQ (for instance, the longer an ITQ is in place in a given fishery, the less likely

that fishery is to collapse). All of these mechanisms would lead to differences between ITQ and non-ITQ fisheries, but only the last mechanism implies a benefit from the management change.

An initial regression of the data in Fig. 1 suggests that implementing an ITQ reduces the probability of collapse by 13.7 percentage points (23). Because ITQs have been disproportionately implemented in a few global ecosystems such as Alaska, Iceland, New Zealand, and Australia (25), regional or taxonomic biases could generate misleading results. To account for potential selection bias, we used a variety of estimation strategies: (i) We restricted the sample to only those ecosystems or taxa that have experienced ITQ management. (ii) We used propensity score methods to match ITQ fisheries to appropriate control fisheries (26). (iii) We used fixed-effects estimation to identify the benefit of ITQs within each fishery.

The results are remarkably similar across all specifications and estimation techniques (23). The propensity score results are summarized in Table 1. Consistent with Fig. 1, ITQ fisheries perform far better than non-ITQ fisheries. Switching to an ITQ not only slows the decline toward widespread collapse, but it actually stops this decline. Each additional year of being in an ITQ (row 2 of Table 1) offsets the global trend (0.5%

increase) of increasing collapse in non-ITQ fisheries (23). Other estimation techniques suggest even larger benefits. For example, fishery fixed-effects results suggest that ITQs not only halt the trend in global collapse, but they may actually reverse it (23).

Although bioeconomic theory suggests that assigning secure rights to fishermen may align incentives and lead to significantly enhanced biological and economic performance, evidence to date has been only case- or region-specific. By examining 11,135 global fisheries, we found a strong link: By 2003, the fraction of ITQ-managed fisheries that were collapsed was about half that of non-ITQ fisheries. This result probably underestimates ITQ benefits, because most ITQ fisheries are young.

The results of this analysis suggest that well-designed catch shares may prevent fishery collapse across diverse taxa and ecosystems. Although the global rate of catch-share adoption has increased since 1970, the fraction of fisheries managed with catch shares is still small. We can estimate their potential impact if we project rights-based management onto all of the world's fisheries since 1970 (Fig. 2). The percent collapsed is reduced to just 9% by 2003; this fraction remains steady thereafter. This figure is a marked reversal of the previous projections.

Despite the dramatic impact catch shares have had on fishery collapse, these results should not be taken as a carte blanche endorsement. First, we have restricted attention to one class of catch shares (ITQs). Second, only by appropriately matching institutional reform with ecological, economic, and social characteristics can maximal benefits be achieved. Nevertheless, these findings suggest that as catch shares are increasingly implemented globally, fish stocks, and the profits from harvesting them, have the potential to recover substantially.

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# Parasite Treatment Affects Maternal Investment in Sons

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Parasitism can be a major constraint on host condition and an important selective force. Theoretical and empirical evidence shows that maternal condition affects relative investment in sons and daughters; however, the effect of parasitism on sex ratio in vertebrates is seldom considered. We demonstrate experimentally that parasitism constrains the ability of mothers to rear sons in a long-lived seabird, the European shag *Phalacrocorax aristotelis*. The effect contributes to the decline in offspring survival as the breeding season progresses and hence has important population-level consequences for this, and potentially other, seasonal breeders.

One key ecological factor influencing the condition of parents, and therefore the potential fitness of dependent offspring, is parasitism (*1*). In sexually dimorphic species, offspring of the larger sex often require higher nutritional investment and are more vulnerable to changes in parental condition (*2*). Moreover, sex allocation theory predicts that parents in good condition should bias investment toward offspring of the sex that stands to gain more from extra resources provided at critical developmental stages (*3*). We provide experimental evidence that parasites can constrain the ability of mothers, in particular, to rear offspring of the more expensive sex. This contributes to differential mortality of sons and daughters as the breeding season progresses and could explain the seasonal decline in offspring survival that is commonly observed in this and many other seasonal breeders.

Populations of the European shag *Phalacrocorax aristotelis* frequently suffer from severe infections of gastro-intestinal parasites, in particular anisakid nematodes [*Contracaecum rudolphi* and *Anisakis simplex* (*4*)]. Although their effects are usually sublethal, these parasites compete with the host for nutrients and trigger costly immune responses (*5*) that may impair host breeding success. Shag chicks must be provisioned in the nest for ~50 days by both parents. Male-biased broods require more food than female-biased broods, and male nestlings grow faster, attain higher peak masses at fledging, and are about 20% larger than females as adults (*4*).

We experimentally manipulated parasitism levels in breeding adults just before chick hatching by treating both male and female parents with a broad-spectrum antiparasite drug (ivermectin), which removes gut parasites and prevents reinfection over a period of ~6 weeks and hence for most of the chick-rearing period. Throughout the laying period, nests were randomly allocated to either a treatment group, in which both parents were treated with ivermectin ($n = 34$ nests), or a control (untreated) group in which parents were exposed to natural levels of parasitism ($n = 83$ nests). Treated and control nests were matched for laying date, ensuring an equal spread of laying dates in each group spanning the natural range (~6 weeks). The survival of sons was higher when their parents had been treated (Fig. 1A) [generalized linear mixed model
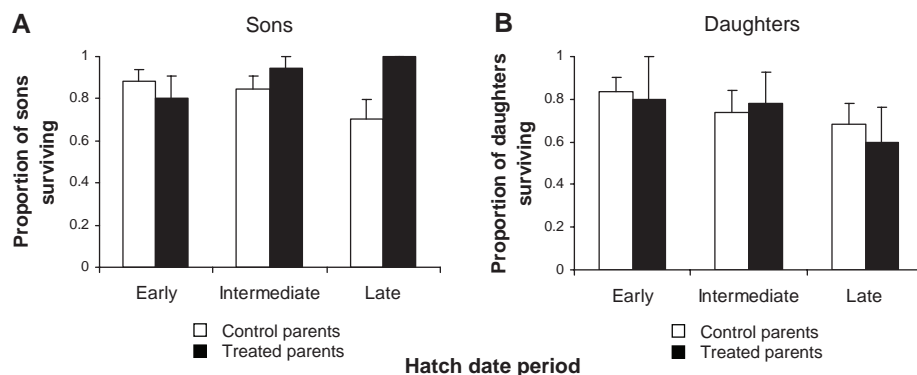
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**Fig. 1.** Differential effect of ivermectin treatment on survival of sons (**A**) and daughters (**B**), and interaction with hatch date. Black bars represent chicks from treated parents, and white bars chicks from control parents. Hatch dates are grouped into early, intermediate and late periods, based on thirds of the distribution and corresponding roughly to 2-weekly intervals. The decline in the survival of sons is not apparent when their parents have been treated. Parasite treatment did not appear to affect the success of rearing daughters. Overall, parasitism in parents accounted for ~37% of the natural seasonal decline in chick survival. Data are means ± SEM. Effect sizes and statistics from logistic regression are given in the text.

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# Supporting Online Material for

## Can Catch Shares Prevent Fisheries Collapse?

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**This PDF file includes:**

**Supporting Online Material: Can Catch Shares Prevent Fisheries Collapse?**

*Christopher Costello, Steven D. Gaines, and John Lynham*

**Statistical Methods**

**Robustness Checks**

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**Statistical Methods**

*Definition of a Fishery*

To match the catch share data with the fisheries yield data from the Sea Around Us Project, fisheries are defined on the scale of the Large Marine Ecosystem (LME). Thus, fish species managed by multiple entities within a single LME are counted as a single fishery. When different institutions are used to manage a species within an LME, we characterize the fishery by the predominant form of management across the LME.

*"First Cut" Estimation*

As a first cut, we pooled all ITQ fisheries into one group (the "treatment" group) and all non-ITQ fisheries into another group (the "control" group). We then estimated the following regression model using ordinary least squares:

$$Pct\_collapsed_{i,t} = \beta_0 + \beta_1 ITQ_i + \beta_2 ITQ\_imp_t + \beta_3 ITQ_i * ITQ\_imp_t + \beta_4 year_t + \varepsilon_{i,t},$$

where $Pct\_collapsed_{i,t}$ is our outcome variable of interest: the Worm et al. (S1) metric of percentage of collapsed fisheries, with $i$ indexing either the ITQ group (the group of fisheries which switched to an ITQ by 2003) or the non-ITQ group (all other fisheries) and with $t$ indexing years from 1950 to 2003. $ITQ_i$ is a dummy variable for the ITQ group. $ITQ\_imp_t$ is a continuous treatment variable representing the rate of ITQ implementation: it is calculated as the fraction of the ITQ group that is currently in an ITQ in year $t$. The first ITQ fishery was implemented in 1975 so $ITQ\_imp_t$ is zero for all years prior to 1975, by 1986 the fraction of ITQs in the database that had been implemented was 0.33, by 1992 it is 0.69 and by 2003 the fraction is by definition 1. $year_t$ is a time variable indicating the relevant year for each observation.

The results are presented in Table S1. There is a statistical difference in the overall level of collapse between the two groups: ITQ fisheries are typically 4.3 percentage points less collapsed than non-ITQ fisheries. The results also suggest that the sample period is correlated with an annual rise in fisheries collapse of 0.49 percentage points per year. This makes sense as the global collapse rate is approximately 27% by 2003. The effect of

implementing ITQs is to reduce the percentage of collapsed fisheries by 13.7 percentage points. The estimated effect is statistically significant at better than the 1% level. Not only is the estimated effect statistically significant, its magnitude is large relative to the maximum percentage of collapsed fisheries in the sample (27.1%). A change of 13.7 percentage points is a substantial difference: it represents, at minimum, a 51% reduction in the percentage of collapsed fisheries. In addition, the statistically insignificant estimate for the coefficient on $ITQ\_imp_t$ suggests that there was no effect of ITQ implementation on the non-ITQ group.

*Fishery Specific Estimation*

We now treat each fishery as a separate cross-sectional observation instead of pooling all the ITQ fisheries in one group and all the non-ITQ fisheries in another group. This leads to a large increase in the degrees of freedom (from 51 to approximately 300,000), allows us to control for observed and unobserved differences between fisheries and to directly measure whether the benefits of ITQs grow with time. Our outcome variable ($collapsed_{i,t}$) is now a zero or one (if collapsed according to the Worm et al. (S1) metric). We no longer use the percentage of ITQs implemented as our treatment variable, instead we use a continuous variable for how many years an ITQ has been implemented in a fishery ($years\_of\_ITQ_{i,t}$). As before, we use a binary variable to indicate whether each fishery is in the ITQ group of fisheries ($ITQ_i$). Since our outcome variable is binary, we estimated the following model using a logit estimator:

$$\Pr(collapsed)_{i,t} = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 ITQ_i + \beta_2 years\_of\_ITQ_{i,t} + \beta_3 year_t\right)}} .$$

We chose this particular specification based on the Likelihood Ratio test results presented in Table S2. The alternative specifications we considered included the following:

$$\Pr(collapsed)_{i,t} = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 pre\_trend_{i,t} + \beta_2 ITQ\_implemented_{i,t} + \beta_3 ITQ_i + \beta_4 years\_of\_ITQ_{i,t} + \beta_5 year_t\right)}} ,$$

$$\Pr(collapsed)_{i,t} = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 ITQ\_implemented_{i,t} + \beta_2 ITQ_i + \beta_3 years\_of\_ITQ_{i,t} + \beta_4 year_t\right)}} ,$$

$$\Pr(collapsed)_{i,t} = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 years\_of\_ITQ_{i,t} + \beta_2 year_t\right)}} .$$

The variable $pre\_trend_{i,t}$ is a time trend variable for ITQ fisheries before the implementation of an ITQ. This tests whether the time trend towards 100% collapse is the same for ITQ and non-ITQ fisheries before the implementation of an ITQ. We find that this pre-trend is statistically identical for both types of fisheries. $ITQ\_implemented_{i,t}$ is a binary variable which equals 1 for all years that a fishery is in an ITQ and zero otherwise. This tests whether or not there is an immediate time-invariant benefit to implementing an ITQ. We do not find an immediate time-invariant benefit. As can be seen in Table S2, the temporal benefit of implementing an ITQ does not change much across the different specifications. The specification in Column (3) of Table S2 (which assumes that ITQ fisheries are, in general, less collapsed than non-ITQ fisheries and that the benefits of

implementing an ITQ accrue over time, not immediately) is the preferred specification. This specification also accords with intuition, bioeconomic theory and the overall picture that emerges from Figure 1 and the First-Cut Estimation. The Akaike and the Bayesian information criterions also support selection of this specification.

*Sample Restriction Estimation*

In an initial attempt to control for potential selection bias (i.e. ITQs were implemented in fisheries that were improving anyway or were more likely to benefit from ITQ management, thus overstating the benefits of ITQs), we restricted our sample to only those fisheries that are likely to share obvious similarities with ITQ fisheries. We first restrict our sample to only those Large Marine Ecosystems (LMEs) that have implemented ITQs by 2003 (the third column in Table S3), then only those genera that have experienced ITQs by 2003 (the fourth column in Table S3), then only those species that have experienced ITQs by 2003 (the fourth column in Table S3) and, finally, all LMEs, genera and species that have experienced ITQs by 2003 (the fifth column in Table S3). The second column in Table S3 is the same as Column (3) in Table S2: it presents results using the full sample.

These results suggest that ITQ fisheries are, in general, 7.1 to 10.8 percentage points less collapsed than non-ITQ fisheries. The effect of each year of being in an ITQ is to reduce the probability of collapse by 0.42 to 0.52 percentage points. The estimated effect is statistically significant at the 1% level or better in all five specifications. The general time

trend towards 100% collapse is estimated to be an increase of 0.51 to 0.59 percentage

points per year. The final row of Table S3 reports the *p*-values from a series of Wald tests

of the null hypothesis that the Annual ITQ Benefit (*years_of_ITQ$_{i,t}$*) is equal in

magnitude but opposite in sign to the Annual Time Trend (*year$_{i,t}$*). For all five samples,

we fail to reject the null that the annual ITQ benefit counters the historical time trend of

increasing collapse. This suggests that ITQs halt the global trend towards 100% collapse.


*Propensity Score Matching*


We also attempted to control for potential selection bias using a propensity score

matching approach (S2). The principle behind propensity score matching is that selection

bias is reduced when the comparison of outcomes is performed using treated and control

groups that are as similar as possible. Since matching on the basis of hundreds of

characteristics is often complex or infeasible, propensity score methods attempt to

summarize the pre-treatment characteristics of each group into a single index (the

propensity score), which makes the matching feasible. Once the index has been

calculated, a researcher can use matching algorithms to match treated groups to their best

controls. Common matching methods include Nearest Neighbor Matching (each treated

observation is matched to the control with the closest propensity score), Radius Matching

(only observations with a control within a certain radius are included in the analysis) and

Kernel Matching (the treated are matched with a weighted average of all controls with

weights that are inversely proportional to the distance between the propensity scores of

treated and controls). An alternative approach to using a matching algorithm is to include

the propensity score as a regressor in a standard regression model. As outlined in Angrist (S3), the differences are largely cosmetic, especially when the estimated conditional probabilities are less than 0.5 (this is the case with the vast majority of our data). In addition, regression estimation is more straightforward to implement and allows for the inclusion of controls that we wish to exclude from the propensity score estimation.

To estimate the propensity scores we estimate the probability that a fishery will be in an ITQ in a given year using four different specifications: (i) a model with a dummy variable for every LME; (ii) a model with a dummy variable for every genus; (iii) a model with a dummy variable for every species; (iv) a model with a dummy variable for every LME, genus and species. We use a logit estimator to estimate the four models for each year in the sample:

$$(1). \ \Pr(ITQ\_implemented)_i = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 LME_1 + \alpha_2 LME_2 + ... + \alpha_L LME_L)}},$$

$$(2). \ \Pr(ITQ\_implemented)_i = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 genus_1 + \alpha_2 genus_2 + ... + \alpha_G genus_G)}},$$

$$(3). \ \Pr(ITQ\_implemented)_i = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 species_1 + \alpha_2 species_2 + ... + \alpha_S species_S)}},$$

$$(4). \ \Pr(ITQ\_implemented)_i = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 LME_1 ... + \alpha_L LME_L + \gamma_1 genus_1 ... + \gamma_G genus_G + \theta_1 species_1 ... + \theta_S species_S)}},$$

where *L* is the total number of LMEs (64), *G* is the total number of genera (687) and *S* is the total number of species (1,179) in the database. The estimated probabilities then provide a year-by-year conditional probability of being selected into ITQ management. Visual inspection of box plots of the propensity scores by ITQ and non-ITQ fisheries suggests that appropriate counterfactuals can be found for each ITQ fishery from the pool of non-ITQ fisheries. Box plots for 2003 are presented in Figure S1 and the full time series is available on request from the authors.

These estimated probabilities (propensity scores) are then included as controls in our regression model:

$$\Pr\left(collapsed\right)_{i,t} = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 ITQ_i + \beta_2 years\_of\_ITQ_{i,t} + \beta_3 year_t + \mathbf{pscores}_{i,t}'\lambda\right)}}$$

The results are presented in Table S4. The second column presents results when no propensity score controls are included. The third column includes propensity scores estimated using LME dummies. The fourth column includes propensity scores estimated using genus dummies. The fifth column includes propensity scores estimated using species dummies. The sixth column includes propensity scores estimated using LME, genus and species dummies together.

The results in Table S4 suggest that ITQ fisheries are, in general, 6.1 to 7.4 percentage points less collapsed than comparable non-ITQ fisheries. The effect of each year of being in an ITQ is to reduce the probability of collapse by 0.37 to 0.54 percentage points. The

estimated effect is statistically significant at the 1% level or better in all five specifications. The general time trend towards 100% collapse is estimated to be 0.54 percentage points per year in all five specifications. The final row of Table S3 reports the *p*-values from a Wald test of the null hypothesis that the Annual ITQ Benefit ($years\_of\_ITQ_{i,t}$) is equal in magnitude but opposite in sign to the Annual Time Trend ($year_{i,t}$). In all five specifications, we fail to reject the null that the annual ITQ benefit counters the historical time trend of increasing collapse. This provides further evidence that ITQs halt the trend towards 100% collapse.

*Fixed Effects Estimation*

In an attempt to control for unobserved time-invariant factors that may be biasing our results, we also ran a series of fishery fixed effects logit models. The results are presented in Table S5. The second column presents the results from estimating the main model with no fixed effects for the full sample. The third column presents results from estimating the main model with fishery fixed effects for the full sample. The fourth column reduces the sample to only those fisheries that have experienced ITQ management and includes fishery specific fixed effects. The fifth column uses the full sample, fishery fixed effects and includes propensity scores estimated using LME, genus and species dummies.

These results suggest that the effect of each year of being in an ITQ is to reduce the *log odds* of the probability of collapse by 10.5 to 12.5 percentage points. The estimated effect is statistically significant at the 1% level or better in all three specifications. The general

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time trend towards 100% collapse is estimated to be an 8.0 to 8.9 percentage points increase in the *log odds* of collapse per year. The penultimate row of Table S5 reports the *p*-values from a Wald test of the null hypothesis that the Annual ITQ Benefit ($years\_of\_ITQ_{i,t}$) is equal in magnitude but opposite in sign to the Annual Time Trend ($year_{i,t}$). In all fixed effects models, we now reject the null at the 10% level or better. The final row of Table S5 reports the *p*-values from a Wald test of the null hypothesis that the Annual ITQ Benefit ($years\_of\_ITQ_{i,t}$) is less than or equal to the absolute value of the Annual Time Trend ($year_{i,t}$). In all fixed effects models, we reject the null at the 5% level or better. This provides strong evidence that ITQs not only halt the trend towards 100% collapse, they actually reverse it.

**Robustness Checks**

*Heteroskedasticity and Autocorrelation*

With any time series analysis, there is concern that the error terms may be autocorrelated. Using the test for autocorrelation in a panel context described by Wooldridge (S4), we detected potential first-order autocorrelation in the majority of our specifications. To test the robustness of our results to this potential bias, we re-ran all of the analyses using Linear Probability Models and panel-adjusted Newey-West standard errors assuming heteroskedasticity and potential first-order autocorrelation. The general magnitude and statistical significance of the estimated coefficients from our main analysis did not

change. In addition, the results from all of the Wald tests comparing coefficients were qualitatively unchanged.

*Difference in Time Trend Before ITQ Implementation*

An assumption underlying our main specification and the interpretation of our results is that the time trend towards 100% collapse is the same for ITQ and non-ITQ fisheries before the implementation of ITQs. If not, then our results may misrepresent the benefits of ITQs. We tested this assumption by using a series of Likelihood Ratio specification tests (as described earlier) and found that there was no statistically significant difference in the pre-implementation time trend for ITQ and non-ITQ fisheries and a model without the $pre\_trend_{i,t}$ variable was preferred. As a further check, we included the $pre\_trend_{i,t}$ variable in all of our main analysis (sample restriction, propensity score and fixed effects). The estimated coefficient on the $pre\_trend_{i,t}$ variable was extremely small and statistically insignificant in all of our main analysis, further confirming that the time trend for ITQ fisheries and non-ITQ fisheries is the same before the implementation of ITQs. Including the $pre\_trend_{i,t}$ variable did not qualitatively alter the estimates of the coefficients of interest or the results of the Wald tests.

*Sensitivity to Excluding Small Fisheries*

The dataset used in Worm et al. (S1) provides equal weight to fisheries regardless of their size. We tested the sensitivity of our main results to (i) excluding fisheries with less than

1,000 tons of catch over the sample period; (ii) excluding fisheries with less than 10,000 tons of catch over the sample period; (iii) excluding fisheries with less than 20,000 tons of catch over the sample period. This has the effect of reducing the sample as follows:

1. There are 5,871 fisheries with greater than 1,000 tons of catch (96 of these are in the ITQ group).
2. There are 3,656 fisheries with greater than 10,000 tons of catch (85 of these are in the ITQ group).
3. There are 3,023 fisheries with greater than 20,000 tons of catch (77 of these are in the ITQ group).

As Figure S2 shows, the finding of Worm et al. (S1) and our main finding still hold. ITQ and non-ITQ fisheries look even more similar (before ITQ adoption) when the sample is restricted to large fisheries. In addition, all of our main empirical analysis is qualitatively unchanged for the different thresholds.

*Potential Endogeneity*

Although we attempted to control for observable differences between fisheries as well as time invariant unobservables, the presence of time varying unobservables might bias our results. This is possible if fishery collapse (or a closely correlated factor) causes a fishery to switch to ITQ management. A solution would be to find an appropriate instrumental variable for ITQ implementation. To date, we have been unable to find appropriate

instruments for ITQ implementation but this remains a promising direction for future

research.

**Figures**

**Figure S1.** Box plots of propensity scores for 2003 based on LME, genus and species dummy regressions.
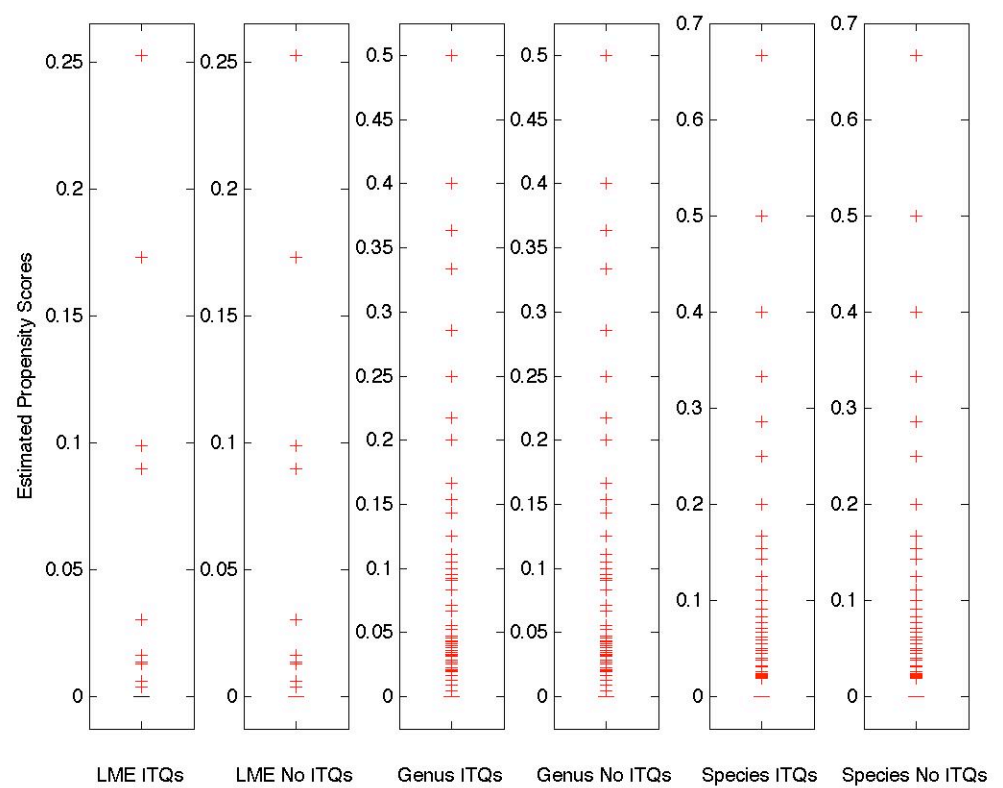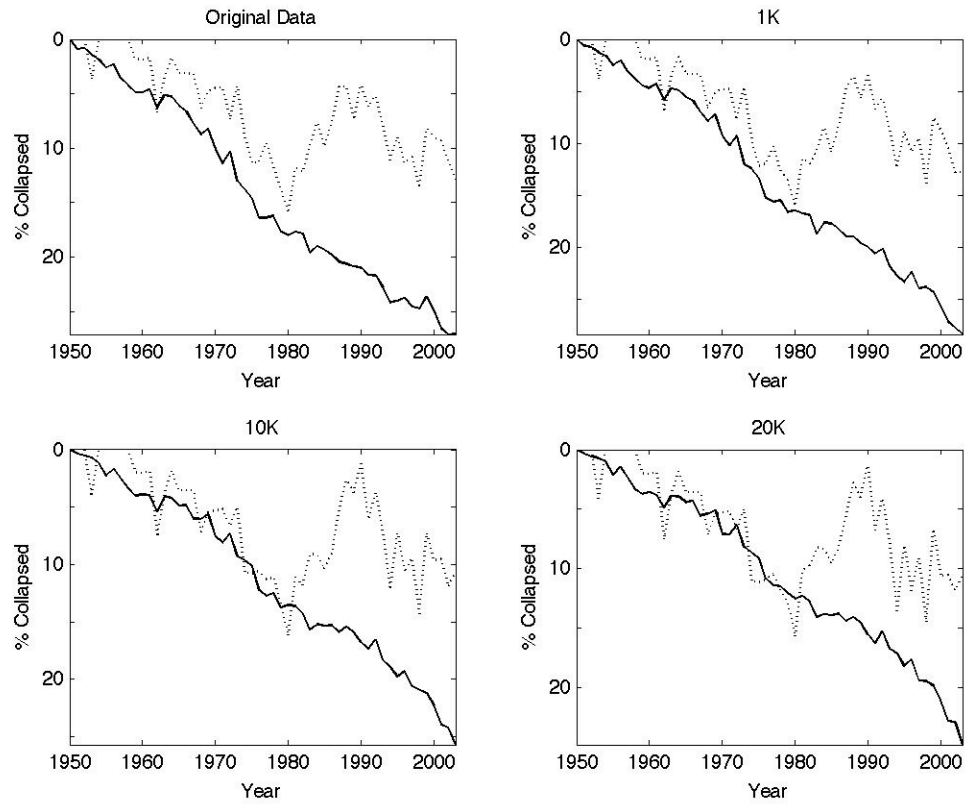
**Figure S2.** Fraction of fisheries collapsed with (dotted line) and without (solid line) management using ITQs for different fishery size cutoffs.



Notes: "1K" restricts the sample to fisheries with greater than 1,000 tons of catch. "10K" restricts the sample to fisheries with greater than 10,000 tons of catch. "20K" restricts the sample to fisheries with greater than 20,000 tons of catch.

**Tables**

**Table S1.** Estimated Coefficients from "First Cut" Estimation.

| Variable | Estimated Coefficient |
|----------|----------------------|
| Intercept | 0.0096* |
| | (0.00565) |
| $ITQ_i$ | -0.0428*** |
| | (0.00505) |
| $ITQ\_imp_t$ | 0.0090 |
| | (0.01255) |
| $ITQ_i *ITQ\_imp_t$ | -0.1367*** |
| | (0.01188) |
| $year_t$ | 0.0049*** |
| | (0.00025) |
| R-squared | 0.92 |
| Observations | 108 |

Notes: Estimated standard errors are presented in parentheses below the estimated coefficients. Three asterisks next to a coefficient indicate that the estimated coefficient is statistically significant at the 1% level. Two asterisks represent the 5% level. One asterisk represents the 10% level.

**Table S2.** Specification Tests.

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $pre\_trend_{i,t}$ | 0.00004 | - | - | - |
| | (0.00084) | | | |
| $ITQ\_implemented_{i,t}$ | 0.0692 | -0.0105 | - | - |
| | (2.25982) | (0.02088) | | |
| $ITQ_i$ | -0.1008 | -0.0694*** | -0.0706*** | - |
| | (0.58091) | (0.00551) | (0.00490) | |
| $years\_of\_ITQ_{i,t}$ | -0.0042** | -0.0042** | -0.0049*** | -0.0137*** |
| | (0.00208) | (0.00208) | (0.00136) | (0.00120) |
| $year_t$ | 0.0054*** | 0.0054*** | 0.0054*** | 0.0055*** |
| | (0.00004) | (0.00004) | (0.00004) | (0.00004) |
| Psuedo R-squared | 0.06 | 0.06 | 0.06 | 0.06 |
| LR | 15269.49 | 15269.48 | 15269.24 | 15134.94 |
| AIC | 251700.3 | 251698.3 | 251696.6 | 251828.9 |
| BIC | 251764.1 | 251751.5 | 251739.1 | 251860.8 |
| $p$-value on LR test | - | 0.9665 | 0.6249 | <0.0001 |
| Observations | 302852 | 302852 | 302852 | 302852 |

Notes: Estimated standard errors are presented in parentheses below the estimated coefficients. Three asterisks next to a coefficient indicate that the estimated coefficient is statistically significant at the 1% level. Two asterisks represent the 5% level. One asterisk represents the 10% level. LR is Likelihood Ratio statistic. $p$-value on LR test is the $p$-value on a Likelihood Ratio test of each model compared to the less restrictive model in the column to the left. AIC is Akaike Information Criterion. BIC is Schwarz's Bayesian Information Criterion.

**Table S3.** Estimated Coefficients from Sample Restriction regressions.

| Variable | Full Sample | LME Sample | Genus Sample | Species Sample | LME, Genus or Species Sample |
|---|---|---|---|---|---|
| $ITQ_i$ | -0.0706*** | -0.0907*** | -0.1084*** | -0.0934*** | -0.1015*** |
| | (0.00490) | (0.00527) | (0.00489) | (0.00508) | (0.00494) |
| $years\_of\_ITQ_{i,t}$ | -0.0049*** | -0.0042*** | -0.0052*** | -0.0052*** | -0.0050*** |
| | (0.00136) | (0.00144) | (0.00147) | (0.00135) | (0.00155) |
| $year_t$ | 0.0054*** | 0.0051*** | 0.0059*** | 0.0057*** | 0.0057*** |
| | (0.00004) | (0.00011) | (0.00009) | (0.00011) | (0.00008) |
| Pseudo $R^2$ | 0.06 | 0.05 | 0.06 | 0.07 | 0.06 |
| LR | 15269.24 | 2358.87 | 4267.57 | 2569.57 | 5649.46 |
| AIC | 251696.6 | 41009.97 | 63763.59 | 34553.29 | 92844.47 |
| BIC | 251739.1 | 41045.05 | 63800.22 | 34587.72 | 92882.63 |
| Observations | 302852 | 47545 | 70109 | 40492 | 102733 |
| $p$-value on test that "$years\_of\_ITQ_{i,t}$ + $years_t$=0" | 0.7231 | 0.5456 | 0.6146 | 0.715 | 0.6137 |

Notes: Estimated standard errors are presented in parentheses below the estimated coefficients. Three asterisks next to a coefficient indicate that the estimated coefficient is statistically significant at the 1% level. Two asterisks represent the 5% level. One asterisk represents the 10% level. LR is Likelihood Ratio statistic. AIC is Akaike Information Criterion. BIC is Schwarz's Bayesian Information Criterion.

**Table S4.** Estimated Coefficients from Propensity Score regressions.

| Variable | No p. scores | LME p. scores | Genus p. scores | Species p. scores | LME, Genus and Species p. scores |
|---|---|---|---|---|---|
| $ITQ_i$ | -0.0706*** (0.00490) | -0.0741*** (0.00428) | -0.0679*** (0.00443) | -0.0687*** (0.00441) | -0.0608*** (0.00472) |
| $years\_of\_ITQ_{i,t}$ | -0.0049*** (0.00136) | -0.0037*** (0.00137) | -0.0054*** (0.00136) | -0.0051*** (0.00139) | -0.0041*** (0.00149) |
| $year_t$ | 0.0054*** (0.00004) | 0.0054*** (0.00004) | 0.0054*** (0.00004) | 0.0054*** (0.00004) | 0.0054*** (0.00004) |
| Pseudo $R^2$ | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| LR | 15269.24 | 15443.23 | 15448.19 | 15529.22 | 15297.01 |
| AIC | 251696.6 | 251580.6 | 251575.6 | 251494.6 | 251706.8 |
| BIC | 251739.1 | 251931.1 | 251926.1 | 251845.1 | 251951.1 |
| Observations | 302852 | 302852 | 302852 | 302852 | 302852 |
| $p$-value on test that "$years\_of\_ITQ_{i,t} + years_t=0$" | 0.7231 | 0.1922 | 0.9697 | 0.8024 | 0.3729 |

Notes: Estimated standard errors are presented in parentheses below the estimated coefficients. Three asterisks next to a coefficient indicate that the estimated coefficient is statistically significant at the 1% level. Two asterisks represent the 5% level. One asterisk represents the 10% level. LR is Likelihood Ratio statistic. AIC is Akaike Information Criterion. BIC is Schwarz's Bayesian Information Criterion.

**Table S5.** Estimated Coefficients from Fishery Fixed Effects regressions.

| Variable | Full Sample | Full Sample with Fixed Effects | ITQ Only Sample with Fixed Effects | Full Sample with Fixed Effects and LME, Genus and Species p. scores |
|---|---|---|---|---|
| $ITQ_i$ | -0.7580*** (0.07204) | - | - | - |
| $years\_of\_ITQ_{i,t}$ | -0.0406*** (0.01117) | -0.1206*** (0.01363) | -0.1048*** (0.01886) | -0.1253*** (0.01761) |
| $year_t$ | 0.0445*** (0.00039) | 0.0888*** (0.00063) | 0.0804*** (0.00747) | 0.0889*** (0.00063) |
| Fixed Effects | No | Yes | Yes | Yes |
| Pseudo $R^2$ | 0.06 | 0.18 | 0.10 | 0.18 |
| LR | 15269.24 | 27544.57 | 160.71 | 27574.91 |
| AIC | 251696.6 | 123430.1 | 1448.551 | 123437.8 |
| BIC | 251739.1 | 123450.4 | 1460.052 | 123650.6 |
| Observations | 302852 | 186554 | 2322 | 186554 |
| $p$-value on test that "$years\_of\_ITQ_{i,t} + years_t = 0$" | 0.7231 | 0.0194 | 0.096 | 0.0387 |
| $p$-value on test that "$years\_of\_ITQ_{i,t} + years_t \geq 0$" | 0.6385 | 0.0097 | 0.048 | 0.0193 |

Notes: Estimated standard errors are presented in parentheses below the estimated coefficients. Three asterisks next to a coefficient indicate that the estimated coefficient is statistically significant at the 1% level. Two asterisks represent the 5% level. One asterisk represents the 10% level. The estimated coefficients are for the rate of change in the *log odds* of collapse as the explanatory variable changes. All previous estimates were for the rate of change in collapse as the explanatory variable changes. To obtain marginal rates of change in a fixed effects setting we would need estimates of any time-invariant unobservables that were removed from the likelihood via the fixed effect logit transformation. This is not possible. LR is Likelihood Ratio statistic. AIC is Akaike Information Criterion. BIC is Schwarz's Bayesian Information Criterion.

**Supporting References**

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