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Using Conditional Lorenz Curves to Examine Consolidation in New Zealand Commercial Fishing

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Abstract *We use individual transferable quota (ITQ) consolidation in New Zealand's commercial fishing to illustrate three different methods of measuring consolidation: the Herfindahl Hirschman Index (HHI), conditional Gini Coefficients, and conditional Lorenz curves. The Lorenz curve allows for conditional specification over stratified groupings, which yields straightforward interpretation and illustration of overall inequality for more nuanced interpretations.*

Key words Lorenz curves, Gini coefficient, Herfindahl Hirschman Index (HHI), consolidation, individual transferable quotas, catch shares, New Zealand.

JEL Classification Codes Q22, Q28, C4.

Introduction

Market-based management approaches, such as individual transferrable quotas (ITQs) and catch share programs, are now well established as an important tool for fisheries managers. At the simplest level, this approach divides the total allowable catch (TAC) among fishers, allowing them to buy and sell this catching right so that the most efficient distribution of the TAC among fishers is achieved. Discussion of ITQs can be found in the literature as early as the 1950s (Gordon 1954; Scott 1955), but emerged as a viable policy tool in the 1980s and 1990s as New Zealand (Dewees 1989; Crothers 1994; Annala 1996) and Iceland (Palsson and Helgason 1995; Eythorsson 2000) adopted national ITQ programs, and other nations, such as the United States and Canada, adopted regional single-species programs (Gauvin, Ward, and Burgess 1994; Buck 1995; Sanders and Beinssen 1997).

In spite of their increasing use, ITQs have remained controversial. One of the primary critiques of ITQs is that they consolidate ownership of catching rights among a few large fishers, rather the catching rights being spread among many fishers with smaller catching capacity, as is often seen in more traditional regulatory approaches. Consolidation attracts academic attention for three distinct reasons: market power, social welfare implications, and governance issues.

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Market Power

Of direct interest to economists is the issue of market power (market concentration and industrial concentration). These issues are well documented in the broader economic literature (Bain 1956; Curry and George 1983; Weiss 1989). As applied to fisheries, the issue is: if ownership of ITQs becomes concentrated among a few players, conditions are favorable for an oligopoly to exert excessive influence in the market. This could be manifested in higher prices paid by consumers or in lower prices the processing companies (which in some fisheries can own a large portion the ITQs) pay to fishers. One study found that the welfare gains associated with ITQs "are reduced and potentially completely offset" in an imperfect market, such as those influenced by consolidation (McEnvoy *et al.* 2009, p. 482). However, research on market power is mixed (Adelaja, Menzo, and McCay 1998; McEnvoy *et al*. 2009) and modeling suggests that market concentration is unlikely to occur (Anderson 1991). Since a primary motivation for ITQ regulation is encouraging market efficiency, and there is some evidence that consolidation is a precursor condition to market power issues, measurement of concentration is an issue worth analyzing, as market and industrial concentration can undermine these objectives.

Social Welfare

ITQs as a social welfare issue are most discussed in the broader fisheries management literature. The critique is that ITQs can shift wealth generated by a fishery and the control of a fishery away from fishers embedded in a local community (Palsson and Helgason 1995) potentially resulting in unemployment (Squires, Kirkley and Tisdell 1995), barriers to entry for new fishers (Palsson and Helgarson 1995), and damage to existing institutions (McCay 2004).

More recently, the issue of "leasing out" ITQs (one entity owning the catching right, while others lease the right to catch it) became associated with consolidation (Stewart and Callagher 2011). As ownership of ITQs concentrates, the practice of leasing grows. Critics argue that rapidly increasing lease prices consume too large a proportion of ex-vessel catch prices, thus illustrating "a market failure preventing...[the] efficiencies that are presumed to go hand in hand with ITQ systems"(Pinkerton and Edwards 2010, p. 1110).[1]

Governance

A more recent concern is the potential for concentration of ITQs undermining fishery self-governance efforts. Within the common-pool resource management literature, there is support of the proposition that ITQs can provide the basis for self-governing regimes (Arnason 2007). However, this presupposes that ITQ owners are also fishers, in which case the long-term profit incentive to manage a fishery sustainably directly impacts those who are actively on the water fishing. Case study work in New Zealand shows that leasing decouples this relationship so that ITQ owners most acutely feel the incentives, while on-the-water fishers who are dependent on leasing do not perceive their direct benefit (Yandle 2008). This, in turn, undermines the potential for ITQs to form the basis of self-management regimes, as ITQ owner and the fisher respond to different incentive structures and do not optimally work together in self-management efforts. Since concentration is associated with increased leasing, understanding concentration is an important first step towards assessing the degree to which this dynamic may threaten fishery self-governance (or co-management) efforts.

[1] For a complete discussion of the strengths and weaknesses of this line of research see: Pinkerton and Edwards 2009, 2010; Turris 2010.)

Analysis

Because of this suite of concerns (market power, social welfare, governance), considerable effort is now invested in devising regulatory structures that limit the degree to which ITQ ownership can consolidate. Examples include: restrictions on initial allocation beyond 10% of TAC (Gauvin, Ward, and Burgess 1994); caps on the maximum amount of quota a single entity may own (van Putten and Gardner 2010); linking quota to vessel size classes (Carothers, Lew, and Sepez 2010); limits on corporate ownership (Carothers, Lew, and Sepez 2010); limits on transferability of quota in the program's initial years (Casey *et al*. 1995); allowing pooling of quota (Abbott, Garber-Yonts, and Wilen 2010), etc. The key point is that these issues are an important critique of ITQ management that is resulting in increased regulation that limits the ability of ITQs to function as originally intended—a mechanism to encourage economically efficient allocation of TAC.

In sum, consolidation is at the root of three key critiques of ITQs: market power, social welfare, and governance. As a result, considerable academic research and regulatory effort is directed to understanding and addressing these issues. With so much effort spent on the effects of consolidation, it is important to ensure that the methods used to measure consolidation are as valid as possible. This is a key first step to better understand the policy dilemmas posed by issues such as market power, social welfare, and governance. This article, while motivated by these issues, focuses on the first step of identifying a robust method for measuring consolidation. Consolidation has emerged as a key issue within ITQ management, and, as such, it is important to identify robust measures of consolidation in order to address the key policy problems raised by this issue.

We use the well-established case of consolidation in New Zealand ITQ ownership with conditional versions of the well-known Lorenz curves. This is a well-established method of measuring inequality that is (to the best of our knowledge) not yet used in fisheries economics. We exploit this relatively new version of the Lorenz curves because it effectively and directly incorporates discrete covariate effects (*i.e*., stratification across markets, locations, or time) and offers familiar and immediate estimation of statistical error. This approach allows a more nuanced assessment than the standard unconditional point estimates of (only) univariate measures of distributional inequality. Below, we place the two dominant means of measuring consolidation in fisheries economics—the Gini Coefficient and the Herfindahl Hirschman Index (HHI)—on similar footing via the empirical cumulative distribution function (ecdf). This perspective naturally, and properly, introduces the empirical Lorenz curve as a version of ecdf, and as the engine for the Gini, HHI, and other indexes. This is followed by an introduction of our case and the associated data. We examine consolidation using all three methods (Lorenz, Gini, and HHI) in the New Zealand commercial fishing industry. Finally, we interpret and compare results.

Methods Review

Empirical studies of distributional inequality typically, though not always explicitly, rely upon a list of sorted data—quantities of 'goods' held by persons or entities— joined with associated observed proportions (Gauven, Ward, and Burgess 1994; Scherer 1970). This is simply the empirical distribution function (ecdf) or the observed cumulative probability distribution. The straightforward method of measuring distributional inequality is to compute this estimate of the ecdf and consider competing measures of inequality as versions of the ecdf, for example the Herfindahl or Gini index. Whether or not the connection to the ecdf is explicit (rare) or implicit (more common), the diagnostic measure of inequality is a scalar, or univariate, that increases as the underlying distribution of the sample is more 'unequal;' *i.e*., further from uniformity.

In brief notation, the data usually considered $\mathbf{y} = (y_1,...,y_n)$ are typically non-negative values; sublimate here an underlying probability model, which may generate the data and consider all of the distributional information in y held by the empirical cumulative distribution function (ecdf):

$$F_n(y) = \sum_{i=1}^{n} \mathbf{1}_{[y_i \leq y]}. \tag{1}$$

Notice that the ecdf in equation (1) generates, at least, n quantiles:

$$F_n^{-1}(p) = y_{(\lfloor p \cdot n \rfloor)}, \tag{2}$$

with $\mathbf{y}_{()}$ the sorted data, the pth quantile is just the $p \cdot n$ th largest observation.

We focus on the representation of the ecdf as arisen from the empirical process. We suppress parametric model specification and view the data only as a sequence of identically distributed, though not necessarily independent, observations (Hoeffding 1948). In fact we expect the data are quite dependent as the consideration of inequality implies a constrained sum or simplexed model (Abayomi, Luo, and Thomas 2010). This is to say that we sublimate any discussion of an underlying parametric/distributional model for the data and consider the data only as arrivals from some null model, and also consider the Lorenz, Gini, and HHI as unbiased (*i.e.*, 'U') statistics.

Lorenz Curves

The Lorenz curve is simply a list of population proportions—numbers between 0 and 1—joined to the list of proportions of 'goods:'

$$L_n(p) = (n \cdot \overline{y})^{-1} \sum_{i=1}^{\lfloor n \cdot p \rfloor} y_{(i)} \tag{3}$$

the observed values of y.

The connection between the Lorenz curve (Lorenz 1905) and the ecdf is immediate; notice that the Lorenz curve, equation (3) is just the ordinary distribution function at an interior point (via its inverse) rescaled by its total over its domain, since $\overline{y} = n^{-1} \sum_{i=1}^{n} F_n^{-1}(i/n)$ [see equation 4]:

$$L_n(p) = (n \cdot \overline{y})^{-1} \sum_{i=1}^{\lfloor n \cdot p \rfloor} F_n^{-1}(i/n). \tag{4}$$

See figure 1 for an illustration of these curves under distributional assumptions. Notice also that the Lorenz curve 'lives' in the region in the lower right triangle of figure 1(a).

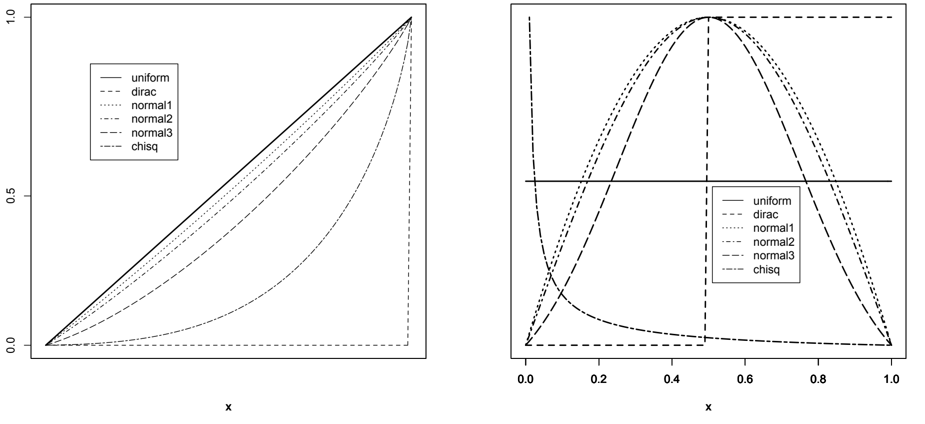

Figure 1. Illustrations of Lorenz Curves on Parametric Distributional Models

Note: The 45° line is the Lorenz curve on a uniform distribution; the right angle is the Dirac distribution, completely concentrated at one point. Example distributions listed in the legend are in order of distributional 'inequality.' The uniform distribution is perfectly equal, the Dirac perfectly unequal, the normal distributions are in order of increasing variance, and the chi-squared distribution is right-skewed. The Gini index is the area between the 45° line—the Lorenz curve for an equal distribution—and the particular Lorenz curve divided by 1/2, the max area of concentration.

Gini Coefficient

The empirical Gini coefficient is a function from an observed distribution to a scalar on the unit interval. The Gini returns the scaled "concentration" of a distribution defined as the ratio of observed distance from equality to the maximum distance from equality. This distance is just the area between the 45° line Lorenz curve for a uniform distribution and the observed Lorenz curve divided by 1/2—the area between a uniform Lorenz curve and a singular Lorenz curve—on the space of the Lorenz curve, the unit square $[0,1] \times [0,1]$. The Gini coefficient is 1, its maximum, on a singular distribution—one where all of the 'good' in a population is held by one person. The minimum, 0, is returned on a uniform distribution—one where everyone in a population holds an equal amount of the good.

There are many ways to calculate Gini's index on a sample of 'goods' y; the coefficient is also defined as a function of the mean deviation, for example. It is illustrative to write it as a function of the Lorenz curve—this illustrates the connection between the univariate Gini, the Lorenz curve, and the observed distribution function as a measure of inequality which was recognized by Gini in his original paper (Gini 1914, 2005). The popular Gini coefficient is but one of several measures of inequality and contributions to statistical inference from Corrado Gini (Forcina and Giorgi 2005).

$$G_n = \frac{\frac{1}{2} - \sum_{p=1/n}^{n} \frac{1}{2} L_n(p)}{1/2} = 1 - 2\tfrac{1}{n} \sum_{p=1/n}^{n} L_n(p) \tag{5}$$

$$= 1 - 2\tfrac{1}{n} \sum_{p=1/n}^{n} (n \cdot \bar{y})^{-1} \sum_{i=1}^{\lfloor n \cdot p \rfloor} F_n^{-1}(i/n). \tag{6}$$

The Gini coefficient is the area just above the Lorenz curve as the distance between the equality of identical data and the inequality observed in the (usually) non-identical data. Figure 1 illustrates prototypical Lorenz curves in contrast with generating probability distributions. In this article we suppress consideration of those distributional models; we consider only those in figure 1(a) as models.

Herfindahl Hirschman Index

The Hirschman/Hirschman-Herfindahl Index, commonly called the Herfindahl index (Hirschman 1964) is defined on data **y** as:

$$H_n = \sum_{i=1}^{n^*} s_i^2. \tag{7}$$

This can be immediately rewritten as:

$$H_n = \sum_{i=1}^{n^*} \left[\frac{y_{(i)}}{n^* \cdot \bar{y}} \right]^2, \tag{8}$$

since it doesn't matter whether the data are sorted, and then again immediately:

$$H_n = \sum_{i=1}^{n^*} \left[\frac{F_n^{-1}(i/n)}{n^* \cdot \bar{y}} \right]^2 = \left[(n^*) \cdot \bar{y} \right]^{-2} \sum_{i=1}^{n} [F_n^{-1}(i/n)]^2, \tag{9}$$

where $n^* = n \wedge 50$ is the minimum of the sample size and fifty.

There has been some expression of preference for the HHI over to the Gini/Lorenz curve in the literature as an 'unbiased' diagnostic for concentration (Gauvin, Ward, and Burgess 1994; Scherer 1970). This preference is specious in the statistical sense of 'biasedness,' as each are functions of ecdf and these estimates (H_n or G_n) on sample data **y** can be expected to converge to its true value as the sample size increases (Martinez-Camblor 2007).

The HHI has been noted to 'inflate' diagnosis of concentration for samples where n is low and the range $y_{(c \cdot n)} - y_{(1)}$ between fractions of the data ($c = 1/n,...,n/n$) is small (Scherer 1970). Generally, since H is a function on $\times_{i=1}^{n}[0,1]^2$ and G is on $\times_{i=1}^{n}[0,1]$, *range* (H) $\leq$ *range* (G) on identical samples y since the squares of numbers on the unit interval are lesser; squares of numbers between zero and one decrease.

A major preference for the Gini coefficient is its direct relationship to the entire Lorenz curve; the HHI can be seen as a thresholded (choosing a cutoff is thresholding) version on the last 50 arbitrary, sorted observations. The Gini/Lorenz duality with the ecdf further yields a conditional approach, which is not straightforward on the thresholded sum of squared shares used in the HHI. Lastly, especially on data with many observations, we expect to find striking differences between the Gini/Lorenz approach and the HHI, with equally divergent implications for policymaking.

New Zealand Commercial Fishing: Setting and Data

Globally, New Zealand is one of the most well-known examples of an ITQ regime. This system regulates commercial fishing within New Zealand's EEZ (roughly 1.2 million square nautical miles or approximately 15 times their land mass), encompassing 130 species and 422,000 tonnes landed in the 2008–2009 fishing year, accounting for 1.49 billion $NZ in exports in 2010 (NZSIC 2011). The industry is comprised of three different fisheries: deepwater, inshore, and highly migratory species (HMS). Top species in the deepwater fishery are orange roughy, squid, and hake, and the sector is dominated by a few vertically integrated harvesting companies. Meanwhile, the commercial inshore industry harvests a diversity of species, and the sector is composed of a mixture on independent small-scale fishers who sell their catch to vertically integrated companies and by boats owned by these companies with hired crews. As the name suggests, HMS are fish that migrate great distances across the Pacific such as tuna, swordfish, and certain shark species. HMS may be fished by either inshore or deepwater fleets and for fisheries management purposes are addressed separately (Starr 2011).

When New Zealand adopted its ITQ regime in 1986, it was one of the first in the world to adopt a national ITQ regime, and it did so with the objective of implementing a system that was as closely aligned as possible with a market-based model. (Detailed histories and analyses of New Zealand's ITQ system can be found in Annala 1996; Batstone and Sharp 1999; Crothers 1994; Yandle and Dewees 2003). At the same time that ITQs were introduced, subsides were removed and minimal restrictions were placed on quota ownership (with the exception of a few specific fisheries). Thus, New Zealand provides an ideal case for examining ITQ ownership patterns.

Existing Evidence on Consolidation in New Zealand

Research on consolidation in the New Zealand fishing industry is significant, with preliminary evidence appearing in the 1990s (Bevin *et al.* 1990; Dewees 1998). Consolidation was first statistically documented in 2000, when a study noting that it was occurring in all sectors except deepwater was published. This study also framed this as a positive, noting that [ITQs] "appear to be living up to the promise of rationalization, albeit at a somewhat more sedate pace in aggregate than some might have imagined in enthusiasm for the concept" (Connor 2000, p. 278). Subsequent studies have examined the effects of ITQs on small-scale fishers (Stewart and Walshe 2008; Stewart, Walshe, and Moodie 2006), and documented a fully functioning market in which profits were increasing due to rationalization/consolidation (Newell, Sanchirico, and Kerr 2005). More recent studies have confirmed that consolidation of catching rights has occurred to varying degrees in both inshore and deepwater fisheries during the earlier years of management (Yandle and Dewees 2008). Furthermore, consolidation of ITQs is shown to occur in all sectors in recent years; while recent annual catch entitlement (ACE) ownership patterns show consolidation for deepwater and mid-water species, but lower levels of consolidation in inshore fisheries (Stewart and Callagher 2011).

Data

As discussed above, New Zealand commercial fishing is well-studied, with clear evidence of consolidation, and provides an excellent case for examining the relative merits of different measures of inequality. After providing a description of the data used in this study, we proceed to this analysis. This study partitions ITQ management into two readily available timeframes: 1987–1990 and 2007–2009. Using these two timeframes allowed us to examine ownership patterns at the start of ITQs and during the most recent years available when this study began. By using multiple years in each partition, we were able to mitigate any single-year anomalies that may have occurred (but we were unaware of). Raw data for the 2007–2009 fishing years was purchased directly from FishServe,[2] while data for 1987–1990 was obtained from Clement and Associates in 1999. This data set was previously used in an unpublished analysis that the company conducted on quota ownership patterns during the first few years of quota management (Clement and Associates 1996).

Methods

In order to ensure that these two datasets were combined appropriately and could be used in this analysis, a few conversions were made. First, in the 1987–1990 timeframe, quota allocation was measured in weight, while in 2007–2009 it was measured in quota shares.[3] Quota weight equivalent (QWE) is the total allowable commercial catch (TACC) for each species and year divided by 10,000 (proportion of total allowable catch). Data from 1987–1990 were converted into quota shares. To ensure that concentration was not artificially deflated and to adjust for clear cases of a single entity holding quota under multiple identities (*e.g.*, identities with similar names and identical mailing addresses), we also updated the dataset to reflect when fishing companies merged.[4] Finally, we removed all quota shares associated with area codes 10 from the analysis, since these areas exist only for administrative purposes.

Conditional Lorenz Curves

Following the work of Aaberge, Bjerve, and Doksum (2005), we look to express the contributions to and differences in inequality in the data—the quota shares, y—across groups; in particular fishery and location partitions. This is straightforward via Aaberge's expression of the overall Lorenz curve in equation (4) across groups as the sum of conditional Lorenz curves on categorical (discrete) covariates for group membership.

This is to set:

$$\Lambda(p \mid \mathbf{x} \in C_j) \tag{10}$$

as the *conditional Lorenz curve* when categorical covariates, **x**, are the group partition, C_j, with C_j, the entire data set; *i.e.,* over a particular partitioning into m distinct groups. In total, the complete or full Lorenz curve can be written as:

$$L(p) = \sum_{j=1}^{m} \pi_j \Lambda(p \mid \mathbf{x} \in C_j) \tag{11}$$

the weighted sum of the group-wise curves. This is merely to express the ordinary, or full, Lorenz curve as an iterated expectation over the group-wise or conditional versions. The trick is to see the group membership, *i.e.*, categorical 'covariates,' as conditional information and fix the contribution of each group-wise Lorenz curve, π_j, so that the expected value is 'unbiased' for overall inequality:

[2] FishServe is "the trading name of a privately owned company called Commercial Fisheries Services (CFS). CFS is a wholly owned subsidiary of SeaFIC (Seafood Industry Council). FishServe provides administrative services to the New Zealand commercial fishing industry to support the 1996 Fisheries Act" (FishServe 2011).
[3] Conversion from weight-based allocation to quota shares was accomplished by first double-checking that quota was measured in kg, then dividing the allocation measured in kg by QWE (quota weight equivalent).
[4] A complete list of these updates is available upon request.

$$E\left[\Lambda(p \mid \mathbf{x})\right] = L(p). \tag{12}$$

This is guaranteed under the following specification:

- set $\pi_j = \frac{\bar{y}_j}{y} \cdot n_j$, the proportional size of group *j*.
- *p* is the proportion of the population, the ordinary argument for *L*(*p*).
- $F_n^{-1}(p)$ is the observed *pth* quantile of *overall* **y**.
- $F_{n,j}(F^{-1}(p))$ is the observed proportion of population in group *j* at the *pth* quantile of the overall distribution.
- $L(F_{n,j}(F^{-1}(p))|C_j$ is the conditional Lorenz curve, for group *j*, on the observed proportion of population in group *j* at the *pth* quantile of the overall distribution.

Thus the iterated sum of the conditional contributions to overall inequality over each group is:

$$L(p) = \sum_{j=1}^{m} \frac{\overline{y}_j}{\overline{y}} \cdot n_j L(F_{n,j}(F^{-1}(p)) \mid C_j). \tag{13}$$

The conditional contributions to the overall Lorenz curve can be expressed via the straightforward algorithm in table 1.

Table 1
Algorithm for Computing Overall Lorenz Curve via Conditional Curves on Categorial Covariates; *i.e.*, Across Groups

1. Sort all the data; Generate the pth quantiles of the unconditioned distribution. In the notation: $F_n, F^{-1}(p)$.
2. Sort the data within each group; Generate the ecdf for each group (conditional distribution) at the *pth* quantiles of the original distribution.
   These are: $F_{n,j}(F^{-1}(p))$.
3. Join the *pth* proportions for each group $F_{n,j}$ with the cumulative proportion of income at each group.This is: $L(F_{n,j}(F^{-1}(p))|C_j$.
4. Compute the contribution to the overall Lorenz curve, at each *pth* proportion:
   $\frac{\bar{y}}{\bar{y}} \cdot n_j L(F_{n,j}(F^{-1}(p)) \mid C_j)$.

This method allows immediate calculation of the overall Lorenz curve as the sum of conditional Lorenz curves. The Gini coefficient, as an immediate transformation of the Lorenz curve (equation (5), above) can be calculated on the overall curve or on the iterated conditional Lorenz curves and then 'averaged' via group contributions π_j.

Confidence Intervals

Straightforward tests for statistical significance can be constructed immediately via the duality between the Lorenz curve and the ecdf in equation (4). It is a well-known result that the ecdf is unbiased for the cumulative distribution function and converges point-wise via the central limit theorem (van der Vaart 1998):

$$F_n(t) \sim N\left(F(t), \tfrac{F(t)[1-F(t)]}{n}\right). \tag{14}$$

Since the Lorenz curve is essentially the ecdf rescaled by n:

$$L_n(p) \sim N\left(L(p), \tfrac{L(p)[1-L(p)]}{n^2}\right) \tag{15}$$

convergence to an 'unbiased' estimate is on the order of n^2. Confidence bounds can then be calculated using ordinary Normal approximations. Point-wise boundaries can be calculated at the observed quantiles using a Normal quantile, $Z_{\alpha/2}$, for desired confidence $1 - \alpha$.

Again, the Gini and HHI are scalar quantities from the *simplexed* ecdf/Lorenz space to the unit interval. As such, confidence intervals for either are not straightforward because of the difficulty in calculating the variance/standard error on the constrained space.

For the univariate measures bootstrapped confidence bounds can be constructed straightaway and should be less conservative than those derived from the overall curve (Mills and Zandvakili 1997; Trede 2002). In practice, null, or hypothesized, values of the distribution function, F, and Lorenz curve, L, may be unavailable. On data of appreciable number, bootstrap intervals, point-wise on each of the p quantiles, suffice as estimators of standard error for the overall and conditional curves. Essentially the curve and its descendants follow a Normal (sampling) distribution with a variance proportional to the true value of the curve. Without an explicit null hypothesis about this true value, or some elicited prior, we can rely on the bootstrap estimate of variance for a plug-in version of the standard error for ordinary Normal confidence limits.

Significant Effects

In direct analogy with ordinary linear regression, desired outputs from models for empirical inequality are the effects of the covariate, **x**, on the measure of inequality. In this setting we have restricted covariates to be categorical groupings, c_j, of the data, and we can generate straightforward estimates of the effect of group membership on overall inequality.

In equivalence with the ordinary regression setup, this 'effect' should be the change in overall inequality given the covariate; *i.e.*, given group membership. Mathematically, this would be:

$$\left.\frac{\partial L(p)}{\partial C}\right|_{C=C_j} = \frac{\partial}{\partial C}\left.[\sum_{j=1}^{m}\frac{\overline{y}_j}{\overline{y}}\cdot n_j L_n(F_{n,j}(F_n^{-1}(p))\,|\,C_j)]\right|_{C=C_j} \tag{16}$$

and involves the Jacobian (or gradient of the transformation) of the probability transform from the overall p-tiles, $F_n^{-1}(p)$, to the conditional ecdfs, *Fn,j*, an empirical approximation of it.

But for categorical covariates, **x**, expressed as groups/partitions, $\bigcup_{j=1}^{m} C_j$, we only need to recall the definition of the derivative and that the categorical covariate is 'singular' (*i.e.*, zero when $C \neq C_j$ and one when $C = C_j$) this is just:

$$L_n(p|C_{-j}) - L_n(p|C) \tag{17}$$

the difference in the estimated Lorenz curve calculated on all other groups besides j, $C_{-j} = \bigcup_{j^* \neq j}^{m} C_j$ and the curve calculated on all groups $C = \bigcup_{j=1}^{m} C_j$.

Though these curves $(p, L_n(p|C_{-j}))$ and $(p, L_n(p|C))$ are not independent, approximate confidence limits for significance at $1 - \alpha$ can be constructed using the sum of the variance of each (under a null hypothesis of no difference in inequality for group j) or more preferably using the bootstrap point-wise on the observed quantiles (Biewen 2002; Efron 1979). For an explicit test of differences in inequality we may assume *a priori* that data across conditional (here fishery, location, time) specifications are equivalently unequal and proceed. In this setting, however, we prefer to compute these standard errors via the bootstrap.

Results and Interpretations

We find strong evidence of market consolidation in the distribution of quota shares, measured by Gini, HHI, and illustrated by the Lorenz curve, in both pre (1987–1990) and post (2007–2009) periods. Generally, though not uniformly, there are significant differences in the Ginis and HHIs between the pre and post periods; the measured concentrations on data from 2007–2009 are greater, often significantly so.

We consider three data partitions $C = \bigcup_{j=1}^{m} C_j$; *i.e.*, three different conditional and overall distributions of the empirical Lorenz curve $L_n(p)$ on the data, **y**, in the presence of categorical covariates, x, across several species of fish, locations, and species designated for export or domestic consumption. In context with equations (16) and (17), we construct confidence intervals at $\alpha = .05$ using the bootstrap. These confidence intervals yield *ad ho*c tests of significant effects for the groupings across fisheries, locations, and exports. The curve-wise confidence intervals yield illustrations of the distribution of inequality that can be quickly viewed, with significance of difference depicted at each of the *pth* quantiles on the curve. For example, in figure 2 the point-wise confidence bounds over the Lorenz curves for the ‘pre’ and ‘post’ intervals are quite narrow.

Recalling that the Lorenz curve is the share of the good ($L(p)$) at the proportion of the population, p, figure 2 illustrates a significant increase in concentration at the median $p = .5$ over time (between the pre and post periods). The difference in concentration at $p = .9$, however, is not significant. These straightforward and illustrative plots of the curves, with point-wise intervals, yield information with useful implications for policymakers. It appears that concentration has generally increased—which is apparent from confidence intervals on either the Ginis or HHIs—but perhaps less so, or not, for the largest shareholders (figure 2).

Each of these tests via equation (17) is significant for the entire curve. This is essentially equivalent to computing the significance of the difference between the conditional and overall Gini (or HHI) indexes. Below we include illustrations of the conditional Lorenz curves and overall indexes across fisheries and overall indexes across location and export categorization (table 2).

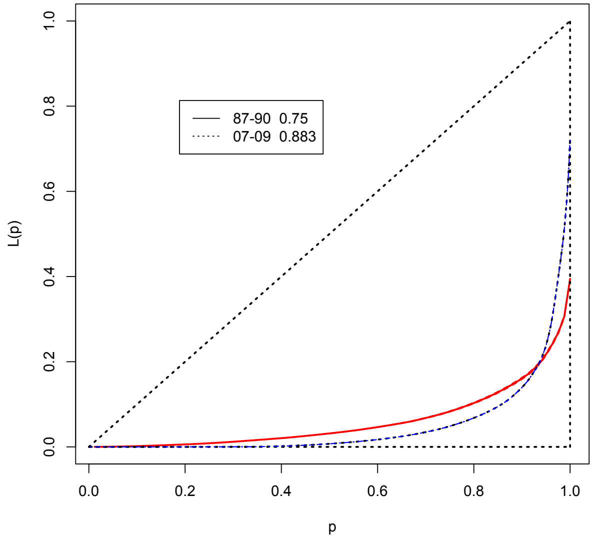

Figure 2. Lorenz Curves for Quota Shares, All Fisheries, with Ginis

Note: Lorenz curves—over all locations—with 95% confidence bars on quota shares for SNA, BCO, ORH, and CRA. The solid curve is on data from 1987–1990, the dashed curve on 2007–2009. There is statistically significant evidence of an increase in concentration, over time, measured over the entire quota share distribution via Lorenz curve and on the Gini index of concentration (included in legend).

Across Fisheries

Figure 2 illustrates the overall Lorenz curves for quota shares in the pre and post periods, 1987–1990 and 2007–2009, across four important fisheries (table 2). The level of concentration for these fisheries was high (an observed Gini of .75) in the pre interval and higher still in the post interval (Gini .883). The plots of the Lorenz curve illustrate reversing difference in concentration at the higher quantiles. The observed curves intersect at p = .92—the 92nd quantile—suggesting concentration is a bit lower in the post period for the larger shareholders.

Table 2
Categorical Variables

Variable	Category	Description
Location	Inshore	Close to shore
	Deepwater	Offshore
	HMS	Highly migratory species
Market	Top export	Rock lobster, Hoki, Squid, Orange roughy, Jack mackerel
	Not top export	All other species
Fishery	SNA	Snapper
	BCO	Blue cod
	ORH	Orange roughy
	CRA	Rock lobster

Figure 3 illustrates the conditional Lorenz curves across fisheries with the overall curve for the pre period, 1987–1990. Snapper and blue cod are more concentrated than average, while orange roughy and rock lobster are less concentrated than average. The confidence bounds for the conditional curves are negligibly small; each of the curves is significantly different from the overall curve via equation (17). Figure 3 also illustrates an artifact of computing the conditional curve; the range of quota shares of rock lobster is about one-tenth of that for the other fisheries. Since the conditional curve is the observed proportion of population in group *j* at the *pth* quantile of the *overall* distribution, the illustrated curve appears to be *more* concentrated than average because it is artificially extrapolated. The contribution to the overall Lorenz curve, as it is scaled by the ratio of the conditional mean to overall mean, is not affected similarly; the conditional Gini/HHIs are accurate, as they are defined on only the observations in the *jth* covariate grouping.

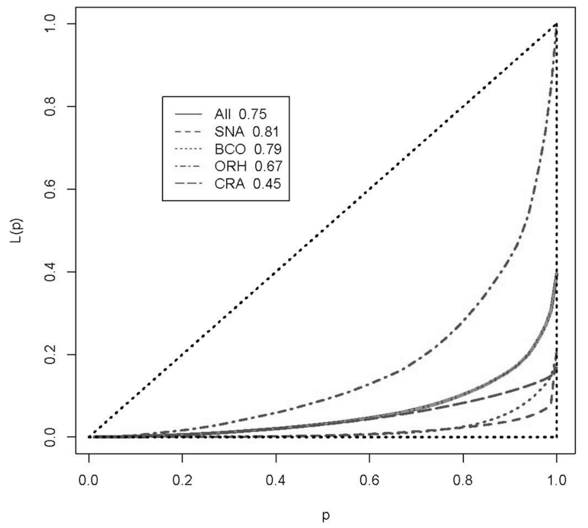

Figure 3. $L(p)$'s on Quota Shares, Across Fisheries, with Ginis: 87–90

Note: Lorenz curves—over all locations—with 95% confidence bars on quota shares for SNA, BCO, ORH, and CRA. The curves are significantly different at $\alpha = .05$ across fisheries (Gini coefficient included in legend).

Figure 4 illustrates the conditional Lorenz curves across fisheries with the overall curve for the post period, 2007–2009. Again the confidence bounds for the conditional curves are so small as to be negligible; the figure illustrates the bounds for the overall curve. The artifact in the rock lobster data is not present. The conditional curve is to the left of the overall curve, and the computed concentration via Gini is less than average. Again we notice strong evidence of consolidation; the observed Ginis are well above .7, and the observed conditional Lorenz curves are at the lower right of the panel. Rock lobster is much more consolidated than in the 'pre' period but still less than overall consolidation.

There are strong apparent differences in concentration between the Gini and HHI indices. The Gini coefficients are uniformly increasing, statistically significantly so, over time from the 'pre' to 'post' period. The HHI for orange roughy increases dramatically from .16 to nearly .97—a measurement of near total market concentration—but the remaining fisheries increase in HHI only slightly and non-significantly. In general, the confidence intervals around the HHI estimate will be wider as the HHI, by definition, is restricted to fewer samples. Also, the observed estimates of HHI are lower in magnitude than the Gini coefficients on the same data. The large increase in HHI for orange roughy may be a data artifact, though the bootstrap confidence interval is not excessively wide (figure 5).

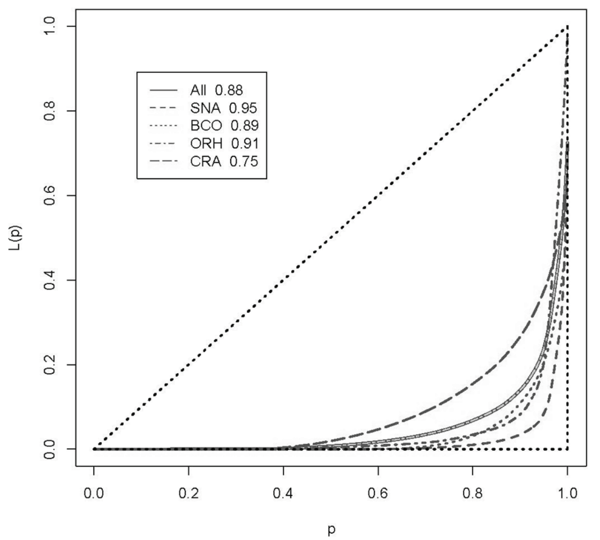

Figure 4. $L(p)$'s on Quota Shares, Across Fisheries, with Ginis: 07–09

Note: Lorenz curves—over all locations—with 95% confidence bars on quota shares for SNA, BCO, ORH, and CRA. The curves are significantly different at α = .05 across fisheries. (Gini coefficient included in legend).

Table 3
Comparison of Gini and HHI Indices

Variable	Category	Gini '87–'90	Gini '07–'09	Sig	HHI '87–'90	HHI '07–'09	Sig?
Location	Inshore	0.69 (0.007)	0.93 (.001)	Y	0.03 (0.02)	0.001 (0.02)	N
	Deepwater	0.70 (.009)	0.82 (0.01)	Y	0.029 (0.01)	0.12 (0.002)	N
	HMS	0.68 (0.025)	0.91 (0.001)	Y	0.012 (0.02)	1.0 (0.04)	Y
Market	Top Export	0.69 (0.01)	0.91 (0.003)	Y	0.002 (0.02)	0.12 (0.02)	Y
	Not Top Export	0.75 (.007)	0.93 (0.001)	Y	0.003 (0.01)	0.002 (0.02)	N
Fishery	SNA	0.81 (0.02)	0.95 (.002)	Y	0.006 (0.04)	0.00 (0.05)	N
	BCO	0.75 (.006)	0.91 (.004)	Y	0.00 (0.001)	0.10 (0.02)	Y
	ORH	0.69 (.021)	0.89 (0.003)	Y	0.12 (0.002)	0.92 (0.01)	Y
	CRA	0.44 (0.001)	0.64 (0.012)	Y	0.02 (0.001)	0.12 (0.004)	Y

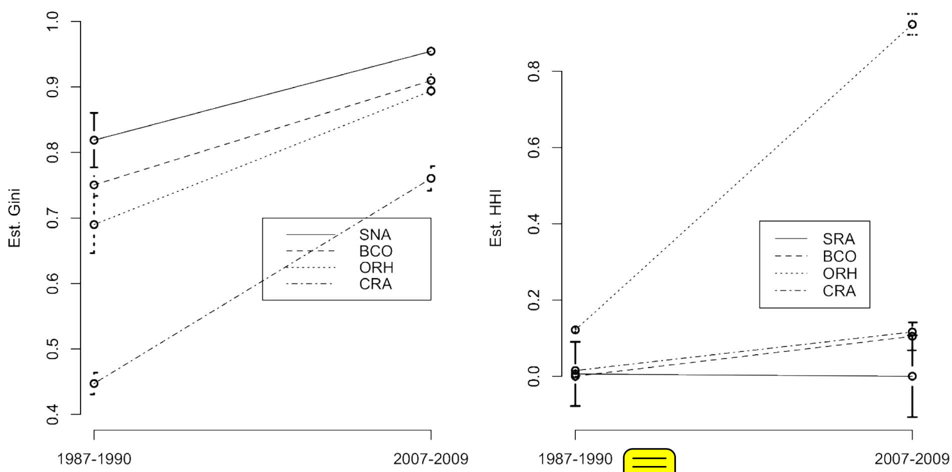

Figure 5. By Fishery Type

Note: Left Panel: Gini indices, past and recent—by fishery type—with 95% confidence bars are calculated by bootstrap. There is statistically significant evidence of an increase in concentration of quota shares. Right Panel: HHI indices, past and recent—by fishery type—with 95% confidence bars calculated by bootstrap. The HHI indices generally have wider confidence intervals. The HHI is defined by a maximum of 50 observations. Notice the difference in ranges (y-axis) for Gini and HHI plots. On data with many observations the HHI is often smaller than the Gini.

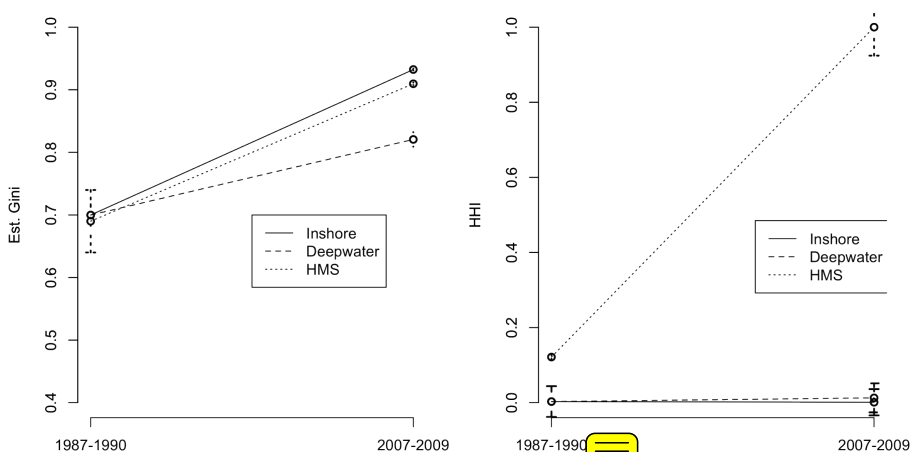

Figure 6. By Location

Note: Left Panel: Gini indices, past and recent—by location—with 95% confidence bars are calculated by bootstrap. There is statistically significant evidence of an increase in concentration of quota shares. Right Panel: HHI indices, past and recent—by location—with 95% confidence bars calculated by bootstrap. There is no significant increase in measured concentration via HHI for inshore and deepwater fish species. In general, the confidence intervals for HHI are wider than the Gini, as they are defined with less data. The observed HHI for Highly Migratory Species (HMS) is nearly maximal. Notice the difference in ranges (y-axis) for Gini and HHI plots. On data with many observations the HHI is often smaller than the Gini.

Across Locations

Figure 6 illustrates significant increases in concentration via Gini over time by classification of fishery species as inshore, deepwater, or highly migratory. The concentration in the ‘pre’ period via the Gini is strong, though not statistically differentiable across this stratification. The observed HHIs, however, appear nearly constant across time, though there is a strong and striking increase in measured concentration for the highly migratory species. The bootstrap confidence interval, however, is quite wide for this large estimate.

Across Exports

Figure 7 suggests a strong, significant increase in concentration for both exported and non-exported fisheries via both Gini and HHI. The observed HHIs are lower, however, and have wider confidence bands for both ‘pre’ (non-significant) and ‘post’ data.

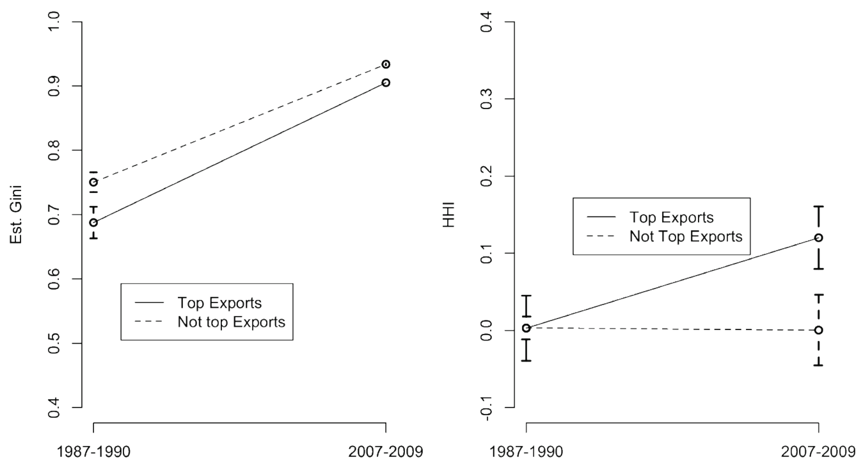

Figure 7. Exports vs. Non-Exports

Note: Left Panel: Gini indices, past and recent—by export type—with 95% confidence bars calculated by bootstrap. There is statistically significant evidence of an increase in concentration of quota shares. Right Panel: HHI indices, past and recent—by export type—with 95% confidence bars calculated by bootstrap. Notice the difference in ranges (y-axis) for Gini and HHI plots. On data with many observations the HHI is often smaller than the Gini.

Conclusion

Appropriately measuring consolidation is an important issue because the literature suggests that it is a precursor for market power and social welfare issues raised by ITQ management. In addition, as ITQs are increasingly looked to as a tool for encouraging self-governance, issues of ITQ allocation become increasingly central to the discussion of how fisheries will be governed. In this article, we use the case of ITQ consolidation in New Zealand to illustrate three different methods of measuring consolidation: the Herfindahl Hirschman Index (HHI), conditional Gini coefficients, and conditional Lorenz curves.

The ecdf unifies the Lorenz curve, the Gini coefficient, and, to a lesser extent, the HHI index. All these measures of concentration are essentially sorted lists of the data (quantiles) with associated proportions (shares). The explicit formulation of the Lorenz curve as a version of the ecdf allows for a conditional specification of the curve as a sum over categorical covariates; *i.e.,* stratified groupings. This approach is especially attractive because it allows straightforward interpretation and illustration of the ‘effect’ of group membership on overall inequality and yields a more nuanced interpretation with perhaps more useful implications.

A fortiori, appealing to the ecdf allows explicit consideration of the error in estimation of the Lorenz curve, Gini coefficient, and again, to a lesser extent, the Herfindahl index. For large data sets, reasonably narrow confidence intervals can be generated using nothing more than bootstrap estimates of variance and the quantiles of the well-known Normal distribution. In a sense, the difference between conditionally specified and full Lorenz curves can be seen as a version of the Kolmogorov-Smirnov (KS) test for distributional differences, as they both rely upon the convergence of the empirical distribution function (Shorack and Wellner 1986; Kolmogorov 1933). An equivalence between this test on the Lorenz curve and the 'scalarization' onto the univariate Gini/HHI may yield more widely applicable methods for measuring (conditional) distributional inequality. Two issues not addressed herein are the conditional specification of the Lorenz curve in the presence of *continuous* covariates and the matter of ordering inequality among intersecting Lorenz curves. The first topic is still relatively open and reliant upon versions of quantile regression (Aaberge, Bjerve, and Doksum 2005)—the second as well—though for our purposes here, significant differences calculated on the Ginis from the Lorenz curves are appropriate (Aaberge 2004).

More careful measures of consolidation of quota (such as we propose) are needed to examine the extent to which consolidation is occurring within a fishery. Appropriate measurement of consolidation (such as the Lorenz curve with its conditional specification) allows for a more nuanced, intuitive interpretation. This is a key first step to untangling the key policy questions raised by ITQs and consolidation.

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