Fishy Business: "Reeling In" and Analyzing the Impact of Climate Change on Groundfish Quota Prices

by

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Abstract

The Northeast United States Multispecies Fishery (NMGF) implemented a catch-share program in 2010. This program, a modified Individual Transfer Quota (ITQ) system, uses self-organized fishermen groups known as sectors to allocate fishing quotas. However, there are transaction costs associated with inter-sector trades of these quotas, which act as barriers to trade and prevent efficient allocation. At the same time, climate change is causing NMGF stocks to relocate both farther north and into deeper waters to escape a variety of unfavorable environmental conditions. Utilizing panel data from 2010 to 2019, this study examines how climate change, in tandem with the aforementioned transaction costs, influenced prices in the NMGF quota market. This study expands on the econometric models used in previous literature to measure NMGF quota market efficacy. Results from the hurdle models and OLS model, respectively, suggest that sea surface heatwaves and the number of stormy days in a fishing year impacted quota prices. While these findings strongly suggest that climate change is influencing NMGF quota prices, they also underline the econometric complexity of discerning market efficiency, especially for an immature market like the NMGF quota market. As climate change continues to affect stocks, and transaction costs prevent efficient allocation, policymakers and regulators face the challenge of preparing the NMGF modified-ITQ system to mitigate potential environmentally induced collapses, ensuring its resilience in the face of climate change.

Keywords: Fisheries management, quota markets, catch shares

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1. Introduction

To achieve the economic and biological goals outlined in the Magnuson-Stevens Act, the Northeast Multispecies Fishery (NMGF) implemented a catch-share program in 2010 (Werner, 2022). This catch-share program is a modified Individual Transfer Quota (ITQ) system. As Lee and Demarest (2023) highlight, ITQ systems have been shown to have many positive attributes for fisheries such as increases to productivity (Färe et al., 2015; Walden et al., 2012; Weninger, 1998), to revenue (Kroetz et al., 2017; Scheld et al., 2012), to profitability (Fox et al., 2003), to output quality (Ardini & Lee, 2018; Casey et al., 1995; Kroetz et al., 2019), to prices (Dupont et al., 2005; Pincinato et al., 2022), to safety (Pfeiffer & Gratz, 2016), and to crew compensation (Abbott et al., 2010; Steiner et al., 2018). These attributes make it attractive to fishery regulators and policymakers because it promises to help reach those goals set forth in the Magnuson-Stevens Act.

ITQ systems are a means to organize fishing efforts and prevent over-fishing (Arnason, 2012; Eythórsson, 1996). ITQs works by assigning individuals the right to fish for a certain stock (Arnason, 2012; Eythórsson, 1996). The definition of a stock is up to the managing body, but generally it is a certain species which has reached sexual maturity in its life cycle. This right to fish for a certain stock is known as a quota, and it acts as an upper bound to the amount of volume (measured in weight) of a stock that a fisherman can catch (Arnason, 2012; Werner, 2022). Fishermen are then allowed to either use their quota or transfer the rights to another fishermen (Arnason, 2012; Werner, 2022).

The particular ITQ system used by the NMGF creates an Annual Catch Limit (ACL) for 20 stocks of 13 species (Vasta, 2019). ACLs represents the maximum volume of a stock that can be fished across all fishermen in a year (Vasta, 2019). The NMGF gives portions of the ACLs, known as Annual Catch Entitlements (ACE), to self-organized fishermen groups known as sectors (Vasta, 2019). Sector managers further distribute ACEs to their sector constituents in whatever manner they deem appropriate (Vasta, 2019). The piece of an ACE that a fisherman receives is that fisherman's quota. The NMGF understands ACE and their distribution are imperfect and allows both inter-sector and intra-sector trading and leasing of these quota allocations, facilitated by sector managers, to promote self-regulation, efficiency, and correct distributional errors (Werner, 2022).

Inter-sector trades are trades that occur between different sectors, while intra-sector trades are trades that occur within the same sectors (Lee & Demarest, 2023). However, there are additional barriers to completing inter-sector trades compared with intra-sector trades. Inter-sector trades require, among other things, that sector managers bargain on behalf of the fishermen from each respective sector (Werner, 2022). This creates additional search and bargaining costs for the fishermen, which leads to higher transaction costs, and thus acts as a barrier to trade (Coase, 1937; Lee & Demarest, 2023). Previous economic literature suggests that this should lead to inefficiencies and non-optimal allocations of these quotas (Arnason, 2012).

Lee and Demarest (2023) have sought to test this claim by considering the determinants of NMGF quota prices. Their research finds that the quota market is largely working as economists would expect. For example, one of the findings of their models is that scarcity of quota matters. Lee and Demarest's (2023) model predicts that abundant quotas are likely to trade at or near zero. However, this research did not consider the impact climate change has had on the quota market. There is a large amount of evidence documenting that climate change effects the managed groundfish populations by shifting species distributions (Hare et al., 2016; Klein et al., 2017; Nye et al., 2009; Pershing et al., 2021). Due to sectors often being organized based on rough geographic fishing location (Werner, 2022), species relocating would imply an increased reliance on the inter-sector quota trade and lease systems for efficient reallocation (Arnason, 2012). However, the previously highlighted transaction costs likely prevent efficient reallocation, and thus lead to higher quota prices.

Building on Lee and Demarest’s (2023) findings and methodology, I examined how climate change has impacted the NMGF quota market. To begin my analysis, I replicated Lee and Demarest’s (2023) models using the same panel data on NMGF quota prices spanning from 2010 to 2019. Lee and Demarest (2023) used three different models: two were hurdle models (one a linear hurdle and the other an exponential hurdle) and one was an OLS model. All three replicated models lead to the same conclusions that Lee and Demarest (2023) arrived at in their research. Then, I introduced six climate change variables into all three models: maximum heatwave temperature recorded (measured at both the sea surface and the bottom surface), duration of the heatwave (measured at the sea surface and bottom surface), and the number days where the wind speed and wave height were large enough that it would be classified as a storm. However, I ran into multicollinearity issues in all models when including all six climate change variables; consequently, in my final climate change models I opted for only considering the sea surface heatwave maximum temperature, the sea surface heatwave duration, and the wave height observations. This led to a drastic reduction in multicollinearity across all models.

In both my linear and exponential climate change hurdle models I found strong evidence that climate change was impacting the price of NMGF quota. I found that the maximum temperature reached at the sea surface during a heatwave was statistically significantly impacting the probability that a quota would trade for a positive price. That is, I found that as heatwave maxima became more extreme, there was a higher probability that a given quota would trade for a positive price. This makes intuitive economic sense when considering how previous literature outlines how heatwaves affect NMGF stocks. Heatwaves drive stocks into colder waters, which means stocks will either travel farther north or into deeper water (Klein et al., 2017; Nye et al., 2009). In turn, this increase to costs for finding and catching these fish gets incorporated into the quota prices. I also found that the duration of a heatwave at the sea surface was probably impacting the price of the quota. That is, I found that as the heatwave duration increased a given stock would trade for a proportionally higher price. This finding also makes sense using similar logic as before. The longer that species moves to escape the heatwave, either farther north or into deeper waters, the harder it is for fishermen to catch the stocks. This translates to higher costs for the fishermen, and the quotas are accordingly adjusted by the market.

In contrast to the conclusions of the hurdle models, the OLS climate model suggests that the number of stormy days in a fishing year is impacting quota prices. That is, the OLS model found that as the number of stormy days increased, the associated prices of NMGF quota decreased. This makes intuitive economics sense and follows the findings of Lee and Demarest (2023). More stormy days means that fishermen must wait to fish, which in turn also likely delays their decision to trade quotas. As Lee and Demarest (2023) found, quota traded later in the year tend to trade for lower prices; implying that as the number of stormy days increased and delayed trading, quota prices tended to be lower, which is what my OLS model found. The stormy days variable reached statistical significance, but it was the only climate change variable the OLS model was confident about.

The statistical significance of different climate change variables in the two different types of models suggests that climate change is impacting the NMGF quota market; but which climate change impact is having the greatest effect is still unclear. This ambiguity provides a potentially fruitful avenue for further research. Regardless, climate change is not going away, nor will it stop affecting the NMGF's stocks in the foreseeable future (Pershing et al., 2021). Therefore, the same policymakers and regulators who instituted the catch-share program are left with the difficult task of preparing the NMGF modified-ITQ system for the effects of climate change, to ensure that it does not collapse like other fisheries in the Gulf of Maine have in the past.

2. Literature Review

Lee and Demarest (2023) published the most recent research examining the catch-share program used by the NMGF. In their research, Lee and Demarest (2023) conducted a two-staged analysis where they first estimated the price per pounds of quota for each stock. Then, they estimated how various characteristics of the quota market (such as output price, quota availability, etc.) impacted the prices of traded quota. In their estimations, they considered all stocks manged by the NMGF from 2010 to 2019. From this research they hoped to understand the determinants of quotas prices and whether the NMGF quota market was "healthy" (Lee & Demarest, 2023).

For their first stage, Lee and Demarest (2023) used a linear hedonic model to determine the implied price per pound of quota. This method has been previously used for analyses in both the NMGF (Murphy et al., 2018) and fisheries in British Columbia (Holland, 2013). This price per pound of quota is then used as the dependent variable in their second stage, estimation of what affected the prices of traded quota. Lee and Demarest (2023) employed both an OLS regression and two variations of Cragg's (1971) hurdle model to determine which variables affected quota prices.

Their OLS model considered live price, quota remaining, fraction of catch observed, distance and inverse distance lag of quota remaining, and the quarter of the fishing year. No non-linear terms were considered. Overall, the model fit the data poorly, with an R^2 value of just 0.273. Yet, most of the considered variables were statistically significant.

When discussing their motivations for using a hurdle model, Lee and Demarest (2023) cite one of the quirks of the NMGF catch-share program – inflated zero observations. That is, after estimating the price per pound of quota, Lee and Demarest (2023) found that almost half of their estimated values were zeros. Thankfully, Cragg's (1971) hurdle model lends itself to modeling this type of complex good. Cragg's (1971) hurdle model is a two-part model first modeling the probability of participation and then modeling the outcome probability density. That is, Cragg's (1971) model begins by estimating the probability that a good will trade at all (participation), and then taking that the trade will occur as a given, the model estimates the price for which that good will trade (outcome). The participation component of the hurdle model examines the probability that the quota will trade at a non-zero value with a probit model. Then, the outcome component examines how factors affect fluctuations in observed, positive, quota prices (Lee & Demarest, 2023). This two-stage model lends itself to modeling zero inflated distributions because, in examining price fluctuations (the outcome component), it disregards the zero-count data allowing researchers to examine what drives price fluctuations. At the same time, in the model output, the model describes to researchers what drives the good (in this case quotas) to trade for a positive price instead of a zero price. This helps give a more complete picture of the market, without being overly influenced by the zero-count data.

For the participation component, Lee and Demarest (2023) considered quota remaining, fraction of quota remaining, fraction of catch observed, and an indicator variable for quarter of the fishing year as explanatory variables. While for the outcome component, Lee and Demarest (2023) considered quota remaining, fraction of quota remaining, fraction of catch observed, indicator variable for quarter of the year, inverse distance and distance of weighted spatial lags of quota remaining as explanatory variables.

Lee and Demarest (2023) used two variations of Cragg's (1971) hurdle model: a linear and an exponential. The participation component of both models is identical; however, the outcome component differs. In the linear hurdle model, the outcome component uses a Gaussian distribution. That is, the linear model assumes the data on quota prices follows a Gaussian distribution and fits its predictions accordingly. While in the exponential hurdle model the outcome component uses a log-normal distribution. That is, the exponential model assumes the data on quota prices follows a log-normal distribution and fits its predictions accordingly.

The linear and exponential hurdle models Lee and Demarest (2023) created fit the data similarly, which can be seen in table 1. Both hurdle models have an R^2 value of about 0.34, an AIC around 920, a BIC of about 990, and a Log-Likelihood around -445. Both found only the fraction of catch observed variable in the participation component to be statistically insignificant. In general, both hurdle models fit the data fairly poorly. Yet, from these hurdle models and the OLS model Lee and Demarest (2023) concluded that because some of the variables, such as quota remaining and live price, are statistically significant the quota market has mixed evidence for acting efficiently. And Lee and Demarest (2023) implicitly assume that an efficient market is a healthy one. However, a drawback to this research is that Lee and Demarest (2023) highlight how environmental changes can affect market dynamics (pg. 5) yet, they do not consider any climate change variables in their models. Likely, considering climate change variables can both improve the explanatory power of their models and create a more cohesive, robust, framework to explain the efficacy of the quota market.

In fact, it is not a new idea that climate change may be impacting the NMGF stocks in negative ways. Klein et al. (2017) begins by noting that New England is being abnormally impacted by the environmental changes fueled from increased levels of concentration of carbon dioxide in the atmosphere (Klein et al., 2017; Pershing et al., 2015). This phenomenon is more colloquially known as climate change, and marine ecosystems are not spared of its influence (Hare et al., 2016; Klein et al., 2017; Nye et al., 2009). Climate change affects these marine ecosystems in a variety of ways: by changing temperature and salinity (Salisbury & Jönsson, 2018; Wallace et al., 2018), by changing levels of pH and dissolved oxygen in the ocean (Salisbury & Jönsson, 2018; Siedlecki et al., 2021), and by shifting ocean currents (Klein et al., 2017), just to name a few. These changes negatively impact the development, reproduction, and harvesting of managed stocks in the NMGF (Klein et al., 2017; Pershing et al., 2015, 2021). That is, climate change decreases the likelihood of stock's eggs, larvae, and juveniles from developing fully into adults (Klein et al., 2017). Further, climate change decreases the rates of spawning and recruitment for stocks (Klein et al., 2017). In turn, this leads to decreased levels of fully developed stocks year-over-year, on average (Klein et al., 2017).

However, most fish do not sit (or rather swim) idly while their environment around them changes. Their adaptations are largely to seek ecosystems which replicate pre-climate change conditions (Klein et al., 2017). For some fish this means looking for new ecosystems in northern waters, for others (since these stocks are groundfish) this means looking for new ecosystems in deeper waters (Klein et al., 2017; Pershing et al., 2021). In general, this means that the distribution of the stocks managed by the NMGF has shifted and will continue to shift in the foreseeable future. In turn, this means that fishermen will have a harder time finding where these stocks now reside. Consequently, economic theory predicts that this will lead to a combination of increased costs and decreased profits for each voyage (ceteris paribus), which will be incorporated into the market evaluation of quota and ultimately make them more expensive.

Alternatively, using the logic Arnason (2012), this could lead to an increase reliance on trading as fishermen who are already fishing in those new ecosystems get the quotas from the fishermen who fish in the areas where the fish are leaving; thus, achieving efficient reallocation of the quotas. Arnason (2012) discusses the importance of property rights for fisheries achieving economic efficiency. Specifically, he highlights the challenges faced in achieving perfect property rights in fisheries when compared to a variety of other systems that use natural resources, such as farming and logging. Arnason (2012) claims that there are four factors to judge a good's property rights: exclusivity, durability, security, and tradability (also called transferability). When one of these components are not "perfect," economic efficiency cannot be achieved (Arnason, 2012). This is a problem for fisheries because often by the nature of the good, and the systems used to regulate their use, "imperfect" property rights are implemented. Arnason (2012) notes that while a variety of systems have been used, the ITQ system seems to be the best system, both in theory and practice, at preserving the property rights for fishermen. It is obvious, then, that the effectiveness of fishery management systems in generating efficiency positively depends on their ability to create, maintain, and protect, fishermen's individual property rights (Arnason, 2012). Hence, externalities which act as barriers to the transferability of ITQ's, in any capacity, limit the economic efficiency of those ITQ's. Equivalently, this means that the quotas in the NMGF are non-optimally distributed because of the transaction costs acting as barriers to trade. Further, if climate change does lead to an increased reliance on trading to get the quota to where the fish are, this will lead to more inefficiencies as transaction costs compound between fishermen.

3. Economic Model

The cornerstone of this research is Cragg's (1971) hurdle model. Lee and Demarest (2023) used both the linear and exponential versions of this model in their analysis of NMGF quota market efficiency. We can define both version of Cragg's (1971) hurdle model by first considering a probit analysis model where the probability that an event will occur at t, $p(E_t)$, is given by

$$p(E_t) = \int_{-\infty}^{X'_t\beta} (2\pi)^{-\frac{1}{2}} \exp\{-z^2/2\}dz. \qquad (1)$$

where X_t is a $K \times 1$ vector of the values of the independent variables at observation t and β is a vector of coefficients (Cragg, 1971). Then, Cragg (1971) designates the cumulative unit normal as

$$C(z) = \int_{-\infty}^{z} (2\pi)^{-\frac{1}{2}} \exp\{-t^2/2\}dt. \qquad (2)$$

Let q_t be defined the desired acquisition of a commodity and let y_t be defined as the actual acquisition of the same commodity, both at t. We can generate q_t as

$$q_t = X'_t\gamma + \epsilon_t \qquad (3)$$

where γ is a vector of coefficients and ϵ_t is independently and normally distributed, with mean zero and variance σ^2 (Cragg, 1971). In a perfect market, the following statements hold: if $q_t \leq 0$ then $y_t = 0$ and if $q_t > 0$ then $q_t = y_t$, which should make intuitive sense (Cragg, 1971).

Simply put, these statements say that agents who do not want a good will not buy a good (if $q_t \leq 0$ then $y_t = 0$), and agents who do want a good will buy the amount of the good that they desire (if $q_t > 0$ then $q_t = y_t$). However, a principal motivator for this research is to examine how transaction costs impact fishermen's ability trade quota and the impact this has on quota prices. Transaction costs imply that there exists $q_t > 0$ such that $y_t \neq q_t$ (Cragg, 1971). We can then express the probability that $y_t = 0$ as

$$f(y_t = 0|X_{1t}, X_{2t}) = C(-X'_{1t}\beta) \qquad (4)$$

where X_{1t} and X_{2t} are vectors of independent variables at observation t (not necessarily distinct), and β is a vector of coefficients (Cragg, 1971). Cragg (1971) neglects to note that the vector X_{1t} is actually the vector of considered variables in the participation component of the hurdle model. Similarly, the vector X_{2t} is the vector of considered variables in the outcome component of the hurdle model. Correspondingly, the density for values of y_t, which has been truncated to consider only positive values, is given by

$$f(y_t|X_{1t}, X_{2t}) = (2\pi)^{-\frac{1}{2}}\sigma^{-1}\exp\{-(y_t - X'_{2t}\gamma)^2\}/\sigma^2\}C(X'_{1t}\beta)/C(X'_{2t}\gamma/\sigma) \qquad (5)$$

for $y_t > 0$. In equation 5, γ is defined to be a vector of coefficients corresponding to the vector X_{2t} (Cragg, 1971). Thus, in the model's output, β and γ are the associated weights for the consider variables in X_{1t} and X_{2t}, respectively. Thus, equation 3, equation 4, and equation 5 outline Lee and Demarest's (2023) linear hurdle model.

With some minor tweaks Cragg (1971) outlines Lee and Demarest's (2023) exponential model. To start, an exponential model assumes that,

$$\log y_t = X'_{2t}\gamma + \epsilon_t \qquad (6)$$

where ϵ_t is normally distributed, and y_t is non-zero (Cragg, 1971). This still implies that equation 4 holds. However, equation 5 becomes

$$f(y_t|X_{1t},X_{2t}) = (y_t)^{-1}(2\pi)^{-\frac{1}{2}}\sigma^{-1}\exp\{-(\log y_t - X'_{2t}\gamma)^2/2\sigma^2\}C(X'_{1t}\beta). \qquad (7)$$

Thus, equation 6, equation 4, and equation 7 outline Lee and Demarest's (2023) exponential hurdle model.

4. Empirical Strategy

4.1 Data

There were two sources of data used in this analysis. The first source of data was directly from Lee and Demarest's (2023) research. They have kindly published all non-confidential data from their research onto GitHub for anyone to access. This means that they have published their estimates for the live price per pound of quota for all stocks from 2010-2019, and all of their data used in the second stage analysis. In exploring their estimates for per pound price of quota, one can easily recognize the attraction of using Cragg's (1971) hurdle model; having models which can factor in, but not be overly influenced by, observations of data at 0 is important for this data set.

Consider both figure 1 and figure 2. Both of these figures vividly demonstrate the abundance of 0's in this data set. Using more normal econometric modeling techniques, such as an OLS, will likely not give a very accurate picture. Take, for example, figure 1. An OLS model would be heavily influenced by the 0's and predict most quotas to trade at or near zero. In addition, and OLS model for figure 1 would likely never be able to predict a quota price of at least $2. Yet, we see this as not uncommon occurrence in the data. Similarly, an OLS model would never be able to predict the extreme values of less than -$2 on the log scale in figure 2. These scenarios perfectly encapsulate the advantage of employing the hurdle models. Hurdle models separate their predictions of the 0's and the rest of the distributions so that they can both make better predictions and tease out what variables underline the different processes. As a note, in figure 2, the 0's have been artificially added back into the data set. That is, the natural logarithm is taken of quota prices, which for the 0's becomes negative infinity. However, I changed those values from negative infinity back to 0 because it is impossible to demonstrate negative infinity on a distribution graph, and the distribution which includes 0's with the log values is exactly what the exponential hurdle model is trying to calculate.

The other source of data is known as the State of the Ecosystem; it is a database published and maintained by the National Oceanic and Atmospheric Administration (NOAA), and it has a variety of environmental panel data sets. This database was accessed through the "ecodata" R package, which makes interfacing with the database much easier. Specifically, from the ecodata package, I used the "bottom_temp," "sst," "heatwave," and the "storms" data sets. The "heatwave," "bottom_temp," and "sst" data sets describe the temperature of the Gulf of Maine (GOM) and surrounding marine regions during heatwaves year-over-year. While the "storms" data set records the wind speeds and wave heights throughout the year to describe when storms have occurred in the GOM and surrounding marine regions. Stocks, which are identified in Lee and Demarest's (2023) data, belong to either the GOM or George's Bank (GB) regions. Thus, while the heatwave and storm data are collected for a variety of different marine regions in the Northeast Continental Shelf, I only consider the data collected for the GOM and GB because stocks managed by the NMGF, currently, only reside in one of those two regions.

Exactly what climate change variables were considered, and why, is discussed in Section 4.2.1. However, to achieve a better sense of what the climate change data looks like, I explore the variables here. Therefore, consider one of the variables of interest which is the maximum temperature reached during a heatwave, shown in the time series plot, figure 3. In figure 3 the red points represent measurements at the sea surface. These measurements show the maximum temperature reached, above what would normally be expected during the heatwave, for heatwaves measure at the sea surface. Exact definitions and models used to determine this are available from NOAA. Also, in figure 3, the blue points represent measurements taken on the bottom surface (the ocean floor). They are defined the same as the red points except the heatwaves are on the bottom surface instead of the sea surface. For both the sea surface temperature (SST) and bottom surface temperature (BST) measurements, there are distinctions made between the locations the measurements were taken. Distinction between heatwaves in the GOM and GB are made by the shape of the scatter-plot point, which are either triangles or circles respectively, to represent each region. In addition, trend lines are also displayed for SST and BST measurements to help aid in following how the SST and BST maxima have fluctuated during the period considered. With the exception of 2019, figure 3 shows that the SST heatwave maxima have been greater than the BST temperature maxima.

Another variable of interest is the duration of heatwaves in a year, which is show in figure 4. For the GOM and GB regions, denoted by circles and triangles respectively as points in the scatter-plot, figure 4 shows the durations (measured in days) of heatwaves throughout the year. The blue points in figure 4 show heatwaves that occur at the bottom surface of the ocean; while the red points in figure 4 show heatwaves that occur at the sea surface. In addition, trend lines are provided to show how, over the period considered from 2010 to 2019, the numbers of days classified as heatwaves has fluctuated. Although it appears that the number of days classified as heatwaves have been decreasing recently (especially for the bottom surface), previous biological literature suggests that this is an anomaly in the trend for the GOM and GB regions (Pershing et al., 2015).

Finally, the last climate change variables which were considered were the number of days classified as a storm due to a combination of wave height and wind speeds recorded. The time series plot for the period considered is shown in figure 5. Similar to both figure 3 and figure 4, the triangles and circles represent the region of measurement, GOM and GB respectively, in figure 5. The orange points in figure 5 represent days where the wind speeds reached levels such that a day was classified as a storm. The purple points in figure 5 represent days where the wave heights reached levels such that the day was classified as a storm. Trend lines are included to show how we see an increased number of storms over the period considered, regardless of measurement technique. From 2010 to 2019, one can easily see that there have been more days that are classified as storms due to the height of the waves than were classified as storms due to the speed of the winds.

4.2 Quota Price Determinants

4.2.1 Hurdle

To begin, I wished to replicate Lee and Demarest's (2023) findings. Replicating their findings ensures that any conclusions I draw from considering climate change comes from the data. Therefore, to replicate their hurdle model I defined t to be a stock in a given fishing year. This means that the following vectors are defined in terms of t, which is to say that they are defined specific for a stock in a given year. Thus, I define the vector X_{1t} to be

$$X_{1t} = [QR \quad FQR \quad FCO \quad Q_1 \quad Q_2 \quad Q_3 \quad Q_4] \qquad (8)$$

where QR is the quota remaining, FQR (calculated as $\frac{QR}{ACE}$) is the percentage of QR compared to the initial ACE allotment, FCO is the amount of live pounds caught while under observation, and Q_n is the nth quarter of the fishing year (for $n \in \{1,2,3,4\}$). Next, I defined the vector X_{2t} to be

$$X_{2t} = [LP \quad QR \quad FCO \quad DLQR \quad DLQR^{-1} \quad Q_1 \quad Q_2 \quad Q_3 \quad Q_4] \qquad (9)$$

where LP is the estimated live price of the stock, $DLQR$ is the distance lag of quota remaining, and $DLQR^{-1}$ is the inverse of the distance lag of quota remaining. To derive the linear hurdle model simply input X_{1t} and X_{2t} into equation 4 and equation 5, respectively. To derive the exponential model simply input X_{1t} and X_{2t} into equation 4 and equation 7, respectively. The estimation of these linear and exponential models can be viewed in table 2. Comparing table 2 to Lee and Demarest's (2023) estimates, one can easily ascertain they are very similar but not exactly the same. The negligible differences in estimates is likely algorithmic and due to differences in modeling software. Lee and Demarest (2023) used STATA for their calculations, while I used R. Regardless of these trivial differences, it is easy to see that using my models leads to the same conclusions as Lee and Demarest (2023). These conclusions are, in essence, that increases in quota remaining decrease the likelihood that quota will trade for a positive price, quota traded later in the year is less likely to trade for a higher price, increases in the live price of the fish suggests higher prices of quota, and increases in quota remaining are associated with decreases in quota prices (Lee & Demarest, 2023). From these data Lee and Demarest (2023) concluded that the market is working efficiently because these findings are what economists would expect to see in a market. However, as highlighted in both section 2 and section 3, climate change has had, and continues to have, drastic impacts on managed stocks. Neglecting to include climate change variables in either of the models from table 2 could lead to overstated levels of normalcy and efficiency in the quota market. Thus, using Lee and Demarest's (2023) replicated models I included climate change variables to examine how these variables impact the conclusions of market normalcy and efficiency.

To begin these updated models, I considered several climate change outcomes. I considered how heatwaves impacted quota prices in a given fishing year. For these heatwaves I considered both their duration and the maximum temperature reached. Further, I segregated these heatwaves by whether the BST or the SST triggered the heatwave measurement. In addition, I also considered number of days in a given fishing year which were categorized as a storm by either their wave height or wind speeds. While the increased occurrence of all six of these variables represents climate change (Agel et al., 2015; Huntington et al., 2016; Klein et al., 2017), they represent two different types of effects on the quota market. The heatwave duration and maximums for both SST and BST represent how climate change is affecting the managed stocks since (I assume) that fishermen do not alter their fishing efforts due to marine heatwaves. However, I do assume that the wind speed and wave height variables impact fishing effort. Namely, that the more severe a storm is in terms of wind speed and wave height, the less likely it is that fishing will occur out of concerns of safety for both crew and equipment. I assume that fish are not affected by either the wave height at the surface or the wind speeds above because NMGF stocks typically dwell close to the bottom of the ocean. Therefore, the heatwave climate change variables represent shocks to the stocks, while the storm climate change variables represent shocks to fishing effort. This gives a more complete picture of how climate change, rather than just how heatwaves, impact NMGF quota prices. I included all six of these climate change variables in both the participation and outcome portions of the hurdle models. This would mean that the vector X_{1t} becomes

$$X_{1t} = [QR \quad \dots \quad Q_4 \quad HW_{BST,Max} \quad HW_{SST,Max} \quad HW_{BST,D} \quad HW_{SST,D} \quad H \quad S] \qquad (10)$$

where $HW_{BST,Max}$ is the maximum BST recorded during a heatwave, $HW_{SST,Max}$ is defined similarly for SST, $HW_{BST,D}$ is the duration of the heatwave recorded from the BST, $HW_{SST,D}$ is also similarly defined but for SST, H is the number of days which were classified as a storm due to wave height, and S is the number of days classified as a storm due to wind speeds.

Using the same definitions as in equation 10, the vector X_{2t} becomes

$$X_{2t} = [LP \quad \dots \quad Q_4 \quad HW_{BST,Max} \quad HW_{SST,Max} \quad HW_{BST,D} \quad HW_{SST,D} \quad H \quad S]. \qquad (11)$$

Then, exactly similar to replicating Lee and Demarest's (2023) models, I plug in the updated X_{1t} and X_{2t} vectors into equation 4 and equation 5 for the linear model, and into equation 4 and equation 7 for the exponential model. The results of including these six climate change variables in both components of each model can be seen in table 3. In sum, I find that including all of the climate change variables does not demonstrate strong evidence that climate change is affecting the quota prices in either the participation or outcome components of the hurdle models. There are a few exceptions to this, such as the wind variable in the participation component, but largely these models find that climate change variables do not appear to affect quota prices. In addition, these models finds that Lee and Demarest's (2023) explanatory variables maintain their sign and statistical significance. Therefore, at first glance it may appear that these models have been created in vain. However, consider that BST and SST heatwave duration and maximum are likely highly correlated since a heatwave would cause all parts of the water-column to become warmer (figure 3). It is also likely that both the wave height and wind speeds are highly correlated since they are both recorded as measurements of storms (figure 5). Thus, it is likely that these models suffer from multicollinearity when including all these variables.

To remedy this multicollinearity, consider the updated X_{1t} and X_{2t} vectors which are defined as

$$X_{1t} = [QR \quad \dots \quad Q_4 \quad HW_{SST,Max} \quad HW_{SST,D} \quad H], \qquad (12)$$

$$X_{2t} = [LP \quad \dots \quad Q_4 \quad HW_{SST,Max} \quad HW_{SST,D} \quad H]. \qquad (13)$$

Where $HW_{SST,Max}$, $HW_{SST,D}$, and H are defined the same as in equation 10 and equation 11. Then input equation 12 and equation 13 into equation 4 and equation 5 for the linear hurdle model, and into equation 4 and equation 7 for the exponential model. The output of these models can be seen in table 4. These models in table 4 remove any multicollinearity present in table 3 by removing one of each of the types of climate change variables.

Initially, it may seem strange to choose SST when the managed stocks are groundfish. That is, the managed stocks are known for staying near the bottom; therefore, it would appear to make more sense to consider BST instead. While it is true that groundfish tend to spend more of their time lower in water column, the data on BST is not as rich or precise as the SST data. SST has been recorded for longer in the “ecodata” database in addition it to being more spatially precise. By “spatially precise” I mean that there are no questions about where in the water column the temperature data was gathered with the SST data set. While with the BST temperature data it is often unclear at what depth the bottom surface temperature was recorded. Because the depth the BST was recorded at is unclear this could lead to measurement error where heatwaves are not properly recorded. Thus, I chose to select a variable that was more sensitive to collecting heatwave data. In addition, I also selected wave height instead of wind speed. I assume that wave height would be a better indicator of whether the fishing vessels would embark since fishing vessels do not rely on wind for operation, but they do rely on waves being within a reasonable height in order to operate their machinery; thus, wave height seemed to be a better proxy for fishing effort.

Using the logic of Lee and Demarest (2023), the new hurdle models in table 4 suggest that climate change is a determinant of quota prices because both SST heatwave duration and temperature are statistically significant in both components of the hurdle models. For example, in the participation component of the models, heatwave maximum has a large magnitude and a high degree of statistical significance, while in the outcome component heatwave duration is the variable with a large magnitude and high degree of statistical significance. Thus, both models are describing that the higher the temperatures reached in a heatwave are associated an increase in the probability that a quota will trade for a positive price. Furthermore, the larger durations of heatwaves are associated with quotas being traded for higher prices. This helps provide some evidence to my hypothesis, which was that climate change is affecting fishermen's ability to find and catch fish and that barriers to trade prevent efficient reallocation, which results in higher quota prices.

4.2.2 OLS

Of course, while the hurdle models were the cornerstone of Lee and Demarest's (2023) analysis, they also consider an OLS model. In their OLS model, they used quota price, QP, as the dependent variable and all the explanatory variables from the outcome component (equation 9) of the hurdle models as the independent variables in their regression. Thus, we can define their OLS model as

$$\begin{aligned} QP = \alpha_0 \quad & +\alpha_1 LP + \alpha_2 QR + \alpha_3 FCO + \alpha_5 DLQR + \alpha_6 DLQR^{-1} \\ & +\alpha_7 Q_1 + \alpha_8 Q_2 + \alpha_9 Q_3 + \alpha_{10} Q_4 + \varepsilon \end{aligned} \tag{14}$$

where LP, QR, FCO, $DLQR$, $DLQR^{-1}$, and Q_n (for $n \in \{1,2,3,4\}$) are defined the same as they were in equation 9, α_0 is the intercept term, $\alpha_1, \ldots, \alpha_{10}$ are the coefficients for each independent variable, and ε is the error term. The output of this regression can be seen in table 5. Similar to the replication of Lee and Demarest's (2023) hurdle models (table 2), my replication is almost identical - signs and statistical significant are almost always the same. However, I do find that the signs on the distance lag and inverse distance lag variables are flipped in my replication. While Lee and Demarest (2023) found that α_5 is negative and α_6 is positive, I find that α_5 is positive and α_6 is negative. Again, the only methodological difference between my replication and Lee and Demarest's (2023) model is software; therefore, it is peculiar to find such a deviation. Regardless, Lee and Demarest (2023) do not spend much time discussing interpretation of $DLQR$ or $DLQR^{-1}$ from the OLS model in their research. Hence, I'll assume that such a difference does not impact the integrity of my replication model significantly. Lee and Demarest (2023) found that while the OLS model does a worse job at explaining variations in quota prices, it reinforces their conclusions that the market is acting as expected. Therefore, they included it as another piece of evidence in their research.

As with their hurdle models, Lee and Demarest (2023) did not consider any climate change variables in their OLS model. Similar to their hurdle models, by not including any climate change variables in their OLS model Lee and Demarest (2023) may be overstating levels of normalcy and efficiency in the quota market. Thus, I included the climate change variables discussed in Section 4.2.1 to their OLS model to see how it impacted their findings. Instead of performing two regressions, one with all six climate change factors considered (which probably suffers from multicollinearity), I elected to only consider the variables in equation 13. That is, I only considered the climate change variables of $HW_{SST,Max}$, $HW_{SST,D}$, and H. Thus, we can define the new OLS regression as equation 14 but including climate change variables,

$$QP = \alpha_0 + \ldots + \alpha_{10}Q_4 + \alpha_{11}HW_{SST,Max} + \alpha_{12}HW_{SST,D} + H + \varepsilon, \qquad (15)$$

where $HW_{SST,Max}$, $HW_{SST,D}$, and H are defined the same as they are in equation 13, and ε is the error term. The output for the model can be seen in table 6.

The output in table 6 is very interesting considering the output from the climate change hurdle models (table 4). It is immediately apparent in this model that our heatwave climate change variables do not have anywhere near the same statistical significance they had in table 4. That is, both the variables $HW_{SST,Max}$ and $HW_{SST,D}$ are not statistically significant, which is the standard that Lee and Demarest (2023) and I have been using to determine whether our respective hypotheses hold any weight. However, my effort-related climate change variable H, which represents days where the wave heights could be classified as a storm, is statistically significant. In fact, the sign of H is negative, which is logically consistent with Lee and Demarest's (2023) findings. Lee and Demarest (2023) found that as quota is traded later in the fishing year it is associated with the quota trading for lower prices. Thus, when storm days delay fishing it is likely this also delays trading, which implies decreasing quota prices. Furthermore, this OLS model finds that Lee and Demarest's (2023) variables are still statistically significant. Therefore, this model (table 6) is suggesting that climate change induced storms are affecting the quota market more than the heatwaves produced by climate change, which initially may appear to be in contrast with the conclusions drawn from the hurdle models (table 4).

In actuality, it is likely the results from table 6 and table 4 complement, rather than contradict, each other. The OLS model considers both zero and positive quota prices when estimating its parameters. Therefore, it considers the entirety of observed quota prices. Meanwhile, the hurdle model can only estimate its outcome component with quota price data which are greater than zero. In turn, this means that my models are describing two similar but different aspects of the quota market. The OLS model is concerned with describing how climate change affects all observed quota prices, while the hurdle models are concerned with describing how climate change affects only the quotas which are already trading for a positive value. Thus, what my model outputs are truly suggesting is that increases in storm days are associated with decreases in quota prices across all quota observations. While increases in duration and maximum temperature of heatwaves are associated with increases in quota prices only for quota which already trade for a positive value.

However, looking at the goodness of fit statistics for Lee and Demarest's (2023) original model, my replication (table 5), and the climate change model (table 6), one can see that these models do not describe the data very well. The R^2 for these models range from a minimum of 0.236 to a maximum of 0.273. The goodness of fit statistics for Lee and Demarest's (2023) original hurdle model, my replicate hurdle model (table 2), and my climate change hurdle model (table 4), are all better than their respective OLS counterparts. That is, the estimated R^2 values are higher in the hurdle models than in the OLS models, but only by a maximum of about 0.25. Thus, although the signs and statistical significance of Lee and Demarest's (2023) variables are preserved in my models, the relatively poor fit of the models should cast doubt on any conclusions of efficiency in the NMGF quota market.

5. Conclusion and Direction for Future Research

Lee and Demarest (2023) investigated whether the NMGF quota market was behaving efficiently and normally. Generally, they concluded that the NMGF quota market was behaving normally, however they did not consider the impact that climate change has on NMGF stocks. Thus, I replicated Lee and Demarest's (2023) models and then included several climate change predictors in their models. I found robust evidence across multiple models that climate change variables are associated with fluctuating prices of NMGF quota. The hurdle models (table 4) highlighted the associated impacts that heatwaves have on quota prices, while the OLS model (table 6) demonstrated the associated impacts of storm days on NMGF quota prices.

The inclusion of climate change predictors in the hurdle and OLS models did not change the significance of the metrics used by Lee and Demarest (2023), however the significance of my climate change variables is suggestive that the market is not acting as normally or as efficiently as Lee and Demarest (2023) portrayed. One of the most obvious culprits of this inefficiency is the barriers to trade created by the sector management system. That is, the requirement to use sector managers to facilitate and complete inter-sector trades. It is well documented that in order for markets to work well they must have many buyers and sellers, perfect information, no barriers to trade, no economies of scale, and minimal transaction costs (Lee & Demarest, 2023). Yet, under the sector management system many of these requirements are violated. For example, there is not perfect information about quota prices since intra-sector trades are not reported. Furthermore, agents willing to trade quota, and at what quantity and price, are only known by their respective sector manager - creating further asymmetric information between potential buyers and sellers. In addition, having to go through sector managers creates transaction costs since it fabricates extra steps beyond the trading parties simply trading. Thus, considering other market trading structures could be fruitful at reducing such inefficiencies. However, this consideration is left to the stakeholders in the NMGF, such as the fishermen and NOAA, since it is their livelihoods that this change would be impacting.

A concern of this research is that quota markets are not a great place for testing market efficiency. There is literature which shows that even mature financial markets struggle to maintain efficient levels at all times (Fama, 1998; Malkiel, 2003). This becomes exacerbated when considering immature quota markets (Pinkerton & Edwards, 2009), such as the NMGF quota market (Lee & Demarest, 2023). Therefore, to ensure that the findings in this research are correct, more data should be considered in the future. The data set used in this paper spans from 2010-2019. At the end of the 2024 fishing year there will 5 more years of data, which represents a 50% increase to the data considered. This would make the market appear more mature to the models and allow for more robust and confident conclusions of market efficiency to be reached. Hence, considering more data is likely one of the most fruitful avenues for further research.

Another direction for further research could be considering other climate change variables. There are many other climate change variables, not considered in this research, which are impacting the Gulf of Maine and surrounding marine regions; these variables have no shortage of data available. For example, harmful algae blooms (Clark et al., 2022; Record et al., 2021), increases in ocean acidification (Salisbury & Jönsson, 2018; Siedlecki et al., 2021), and increases in ocean salinity (Salisbury & Jönsson, 2018; Wallace et al., 2018), are all linked to climate change and have been documented impacting different stocks in the NMGF to varying degrees (Klein et al., 2017). Exploration of these phenomena will help uncover the true impact of climate change on the NMGF quota market.

6. References

Abbott, J. K., Garber-Yonts, B., & Wilen, J. E. (2010). Employment and Remuneration Effects of IFQs in the Bering Sea/Aleutian Islands Crab Fisheries. *Marine Resource Economics*, *25*(4), 333–354. https://doi.org/10.5950/0738-1360-25.4.333

Agel, L., Barlow, M., Qian, J.-H., Colby, F., Douglas, E., & Eichler, T. (2015). Climatology of Daily Precipitation and Extreme Precipitation Events in the Northeast United States. *Journal of Hydrometeorology*, *16*(6), 2537–2557. https://doi.org/10.1175/JHM-D-14-0147.1

Ardini, G., & Lee, M.-Y. (2018). Do IFQs in the US Atlantic Sea Scallop Fishery Impact Price and Size? *Marine Resource Economics*, *33*(3), 263–288. https://doi.org/10.1086/698199

Arnason, R. (2012). Property Rights in Fisheries: How Much Can Individual Transferable Quotas Accomplish? *Review of Environmental Economics and Policy*, *6*(2), 217–236. https://doi.org/10.1093/reep/res011

Casey, K. E., Dewees, C. M., Turris, B. R., & Wilen, J. E. (1995). The Effects of Individual Vessel Quotas in the British Columbia Halibut Fishery. *Marine Resource Economics*, *10*(3), 211–230. https://doi.org/10.1086/mre.10.3.42629588

Clark, S., Hubbard, K. A., Ralston, D. K., McGillicuddy, D. J., Stock, C., Alexander, M. A., & Curchitser, E. (2022). Projected effects of climate change on Pseudo-nitzschia bloom dynamics in the Gulf of Maine. *Journal of Marine Systems*, *230*, 103737. https://doi.org/10.1016/j.jmarsys.2022.103737

Coase, R. H. (1937). The Nature of the Firm. *Economica*, *4*(16), 386–405. https://doi.org/10.1111/j.1468-0335.1937.tb00002.x

Cragg, J. G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, *39*(5), 829. https://doi.org/10.2307/1909582

Dupont, D. P., Fox, K. J., Gordon, D. V., & Grafton, R. Q. (2005). Profit and Price Effects of Multi-species Individual Transferable Quotas. *Journal of Agricultural Economics*, *56*(1), 31–57. https://doi.org/10.1111/j.1477-9552.2005.tb00121.x

Eythórsson, E. (1996). Theory and practice of ITQs in Iceland. Privatization of common fishing rights. *Marine Policy*, *20*(3), 269–281. https://doi.org/10.1016/0308-597X(96)00009-7

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*(3), 283–306. https://doi.org/10.1016/S0304-405X(98)00026-9

Färe, R., Grosskopf, S., & Walden, J. (2015). Productivity change and fleet restructuring after transition to individual transferable quota management. *Marine Policy*, *62*, 318–325. https://doi.org/10.1016/j.marpol.2015.05.015

Fox, K. J., Grafton, R. Q., Kirkley, J., & Squires, D. (2003). Property rights in a fishery: Regulatory change and firm performance. *Journal of Environmental Economics and Management*, *46*(1), 156–177. https://doi.org/10.1016/S0095-0696(02)00027-X

Hare, J. A., Morrison, W. E., Nelson, M. W., Stachura, M. M., Teeters, E. J., Griffis, R. B., Alexander, M. A., Scott, J. D., Alade, L., Bell, R. J., Chute, A. S., Curti, K. L., Curtis, T. H., Kircheis, D., Kocik, J. F., Lucey, S. M., McCandless, C. T., Milke, L. M., Richardson, D. E., … Griswold, C. A. (2016). A Vulnerability Assessment of Fish and Invertebrates to Climate Change on the Northeast U.S. Continental Shelf. *PLOS ONE*, *11*(2), e0146756. https://doi.org/10.1371/journal.pone.0146756

Holland, D. S. (2013). Making Cents Out of Barter Data from the British Columbia Groundfish ITQ Market. *Marine Resource Economics*, *28*(4), 311–330. https://doi.org/10.5950/0738-1360-28.4.311

Huntington, T. G., Balch, W. M., Aiken, G. R., Sheffield, J., Luo, L., Roesler, C. S., & Camill, P. (2016). Climate change and dissolved organic carbon export to the Gulf of Maine. *Journal of Geophysical Research: Biogeosciences*, *121*(10), 2700–2716. https://doi.org/10.1002/2015JG003314

Klein, E. S., Smith, S. L., & Kritzer, J. P. (2017). Effects of climate change on four New England groundfish species. *Reviews in Fish Biology and Fisheries*, *27*(2), 317–338. https://doi.org/10.1007/s11160-016-9444-z

Kroetz, K., Sanchirico, J. N., Galarza Contreras, E., Corderi Novoa, D., Collado, N., & Swiedler, E. W. (2019). Examination of the Peruvian Anchovy Individual Vessel Quota (IVQ) system. *Marine Policy*, *101*, 15–24. https://doi.org/10.1016/j.marpol.2018.11.008

Kroetz, K., Sanchirico, J. N., Peña-Torres, J., & Novoa, D. C. (2017). Evaluation of the Chilean Jack Mackerel ITQ System. *Marine Resource Economics*, *32*(2), 217–241. https://doi.org/10.1086/690771

Lee, M.-Y., & Demarest, C. (2023). Groundfish quota prices. *Fisheries Research*, *260*, 106605. https://doi.org/10.1016/j.fishres.2022.106605

Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, *17*(1), 59–82. https://doi.org/10.1257/089533003321164958

Murphy, T., Ardini, G., Vasta, M., Kitts, A., Demarest, C., Walden, J., & Caless, D. (2018). *2015 Final Report on the Performance of the Northeast Multispecies (Groundfish) Fishery (May 2007 – April 2016)*. https://doi.org/10.25923/vzmy-2y05

Nye, J., Link, J., Hare, J., & Overholtz, W. (2009). Changing spatial distribution of fish stocks in relation to climate and population size on the Northeast United States continental shelf. *Marine Ecology Progress Series*, *393*, 111–129. https://doi.org/10.3354/meps08220

Pershing, A. J., Alexander, M. A., Brady, D. C., Brickman, D., Curchitser, E. N., Diamond, A. W., McClenachan, L., Mills, K. E., Nichols, O. C., Pendleton, D. E., Record, N. R., Scott, J. D., Staudinger, M. D., & Wang, Y. (2021). Climate impacts on the Gulf of Maine ecosystem. *Elementa: Science of the Anthropocene*, *9*(1), 00076. https://doi.org/10.1525/elementa.2020.00076

Pershing, A. J., Alexander, M. A., Hernandez, C. M., Kerr, L. A., Le Bris, A., Mills, K. E., Nye, J. A., Record, N. R., Scannell, H. A., Scott, J. D., Sherwood, G. D., & Thomas, A. C. (2015). Slow adaptation in the face of rapid warming leads to collapse of the Gulf of Maine cod fishery. *Science*, *350*(6262), 809–812. https://doi.org/10.1126/science.aac9819

Pfeiffer, L., & Gratz, T. (2016). The effect of rights-based fisheries management on risk taking and fishing safety. *Proceedings of the National Academy of Sciences*, *113*(10), 2615–2620. https://doi.org/10.1073/pnas.1509456113

Pincinato, R. B. M., Asche, F., Cojocaru, A. L., Liu, Y., & Roll, K. H. (2022). The Impact of Transferable Fishing Quotas on Cost, Price, and Season Length. *Marine Resource Economics*, *37*(1), 53–63. https://doi.org/10.1086/716728

Pinkerton, E., & Edwards, D. N. (2009). The elephant in the room: The hidden costs of leasing individual transferable fishing quotas. *Marine Policy*, *33*(4), 707–713. https://doi.org/10.1016/j.marpol.2009.02.004

Record, N. R., Countway, P. D., Kanwit, K., & Fernández-Robledo, J. A. (2021). Rise of the rare biosphere. *Elementa: Science of the Anthropocene*, *9*(1), 00056. https://doi.org/10.1525/elementa.2020.00056

Salisbury, J. E., & Jönsson, B. F. (2018). Rapid warming and salinity changes in the Gulf of Maine alter surface ocean carbonate parameters and hide ocean acidification. *Biogeochemistry*, *141*(3), 401–418. https://doi.org/10.1007/s10533-018-0505-3

Scheld, A. M., Anderson, C. M., & Uchida, H. (2012). The Economic Effects of Catch Share Management: The Rhode Island Fluke Sector Pilot Program. *Marine Resource Economics*, *27*(3), 203–228. https://doi.org/10.5950/0738-1360-27.3.203

Siedlecki, S., Salisbury, J., Gledhill, D., Bastidas, C., Meseck, S., McGarry, K., Hunt, C., Alexander, M., Lavoie, D., Wang, Z., Scott, J., Brady, D., Mlsna, I., Azetsu-Scott, K., Liberti, C., Melrose, D., White, M., Pershing, A., Vandemark, D., … Morrison, R. (2021). Projecting ocean acidification impacts for the Gulf of Maine to 2050. *Elementa: Science of the Anthropocene*, *9*(1), 00062. https://doi.org/10.1525/elementa.2020.00062

Steiner, E., Russell, S., Vizek, A., & Warlick, A. (2018). Crew in the West Coast Groundfish Catch Share Program: Changes in Compensation and Job Satisfaction. *Coastal Management*, *46*(6), 656–676. https://doi.org/10.1080/08920753.2018.1522495

Vasta, M. (2019). *Network Analysis of the Northeast Multispecies (Groundfish) Annual Catch Entitlement (ACE) Transfer Network (May 2010 – April 2016)*. https://doi.org/10.25923/cnf1-mx82

Walden, J. B., Kirkley, J. E., Färe, R., & Logan, P. (2012). Productivity Change under an Individual Transferable Quota Management System. *American Journal of Agricultural Economics*, *94*(4), 913–928. https://doi.org/10.1093/ajae/aas025

Wallace, E. J., Looney, L. B., & Gong, D. (2018). Multi-Decadal Trends and Variability in Temperature and Salinity in the Mid-Atlantic Bight, Georges Bank, and Gulf of Maine. *Journal of Marine Research*, *76*(5), 163–215. https://doi.org/10.1357/002224018826473281

Weninger, Q. (1998). Assessing Efficiency Gains from Individual Transferable Quotas: An Application to the Mid-Atlantic Surf Clam and Ocean Quahog Fishery. *American Journal of Agricultural Economics*, *80*(4), 750–764. https://doi.org/10.2307/1244061

Werner, S. L. (2022). *An Economic Analysis of the Multispecies Catch Share Program*. https://doi.org/10.25923/ER07-W293

7. Tables

Table 1

Lee and Demarest (2023) Hurdle Model Goodness of Fit Statistics

Goodness of Fit	Exponential	Linear
R^2	0.315	0.367
AIC	916	932
BIC	987	1008
Log Likelihood	-442	-449

Table 2

Lee and Demarest (2023) Hurdle Models Replication

Variable	Exponential	Linear
Quota Remaining [H1]	-0.042	0.030
Fraction Quota Remaining [H1]	-3.530***	-11.334**
Fraction of Catch Observed [H1]	0.625	-4.252^
Q2 [H1]	-0.701***	-1.364*
Q3 [H1]	-0.888***	-0.641
Q4 [H1]	-1.916***	-4.039***
Intercept [H1]	4.050***	13.656***
Live Price [H2]	0.604***	0.996***
Quota Remaining [H2]	-0.139***	-0.223***
Fraction of Catch Observed [H2]	2.341***	7.028***
Distance Lag of Quota Remaining [H2]	0.266**	1.112***
Inverse Distance Lag of Quota Remaining [H2]	-0.332**	-1.156***
Q2 [H2]	-0.114	-0.453^
Q3 [H2]	-0.258**	-0.569*
Q4 [H2]	-0.228*	-0.665*
Intercept [H2]	-0.754*	-2.017***
N	672	672
N[0]	305	305
N[Count]	367	367
R^2[0]	0.342	0.341
R^2[Count]	0.518	0.172
Log Likelihood	-824.798	-898.223

Note: $^{\wedge}\, p < 0.1, ^{*}\, p < 0.05, ^{**}\, p < 0.01, ^{***}\, p < 0.001$

Table 3

All Climate Change Variables Hurdle Models

Variable	Exponential Climate	Linear Climate
Intercept [H1]	4.688***	5.047***
Quota Remaining [H1]	-0.138***	-0.006
Fraction Quota Remaining [H1]	-3.857***	-3.365***
Fraction of Catch Observed [H1]	1.878*	0.002
Q2 [H1]	-0.762***	-0.638**
Q3 [H1]	-1.038***	-0.745**
Q4 [H1]	-2.098***	-1.691***
BST Heatwave Maximum [H1]	0.391	0.745*
SST Heatwave Maximum [H1]	0.239	0.084
BST Heatwave Duration [H1]	-0.004*	-0.005*
SST Heatwave Duration [H1]	-0.007	-0.016
Storm Days (Waves) [H1]	0.041	0.040
Storm Days (Wind) [H1]	-0.183***	-0.210***
Intercept [H2]	-1.720***	-12.279***
Live Price [H2]	0.865***	3.241***
Quota Remaining [H2]	-0.177***	-0.853**
Fraction of Catch Observed [H2]	3.160***	22.034***
Distance Lag of Quota Remaining [H2]	0.198	2.787***
Inverse Distance Lag of Quota Remaining [H2]	-0.286	-2.535**
Q2 [H2]	-0.037	-0.501
Q3 [H2]	-0.437**	-1.576*
Q4 [H2]	-0.362*	-1.198
BST Heatwave Maximum [H2]	-0.120	-3.656**
SST Heatwave Maximum [H2]	-0.220	0.692
BST Heatwave Duration [H2]	0.000	0.008
SST Heatwave Duration [H2]	0.018*	0.101*

Storm Days (Waves) [H2]	-0.037	-0.224
Storm Days (Wind) [H2]	0.125**	0.310
N	672	672
N[0]	305	305
N[Count]	367	367
R^2[0]	0.396	0.406
R^2[Count]	0.454	0.285
Log Likelihood	-827.253	-825.558

Note: ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4

Climate Change SST Hurdle Models

Variable	Exponential Climate SST	Linear Climate SST
Intercept [H1]	4.020***	4.090***
Quota Remaining [H1]	-0.127***	-0.054
Fraction Quota Remaining [H1]	-3.721***	-3.447***
Fraction of Catch Observed [H1]	1.912**	1.064
Q2 [H1]	-0.749***	-0.675***
Q3 [H1]	-1.010***	-0.853***
Q4 [H1]	-2.025***	-1.806***
SST Heatwave Maximum [H1]	0.670***	0.703***
SST Heatwave Duration [H1]	-0.014^	-0.019*
Storm Days (Waves) [H1]	-0.033	-0.031
Intercept [H2]	-1.521***	-10.906***
Live Price [H2]	0.898***	3.629***
Quota Remaining [H2]	-0.203***	-0.896***
Fraction of Catch Observed [H2]	3.094***	-18.910***
Distance Lag of Quota Remaining [H2]	0.221***	2.868**
Inverse Distance Lag of Quota Remaining [H2]	-0.293^	-2.833**
Q2 [H2]	-0.065	-0.668
Q3 [H2]	-0.404**	-1.535^
Q4 [H2]	-0.348*	-1.175
SST Heatwave Maximum [H2]	-0.332^	-1.487
SST Heatwave Duration [H2]	0.015^	0.086^
Storm Days (Waves) [H2]	0.004	-0.177
N	672	672
N[0]	305	305
N[Count]	367	367

R^2[0]	0.365	0.368
R^2[Count]	0.442	0.270
Log Likelihood	-843.291	-843.912

Note: $^\wedge\ p < 0.1, ^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 5

Lee and Demarest (2023) OLS Replication

Variable	OLS
Intercept	-0.478***
Live Price	0.393***
Quota Remaining	-0.005
Fraction of Catch Observed	1.132***
Distance Lag of Quota Remaining	0.340***
Inverse Distance Lag of Quota Remaining	-0.351***
Q2	-0.084
Q3	-0.074
Q4	-0.120^
N	672
R^2	0.236
Adj. R^2	0.227
AIC	1140.175
BIC	1185.278
Log Likelihood	-560.088

Note: $^\wedge\, p < 0.1, ^{*}\, p < 0.05, ^{**}\, p < 0.01, ^{***}\, p < 0.001$

Table 6

Climate Change OLS

Variable	Climate OLS
Intercept	-0.366*
Live Price	0.383***
Quota Remaining	-0.001
Fraction of Catch Observed	1.301***
Distance Lag of Quota Remaining	0.404***
Inverse Distance Lag of Quota Remaining	-0.381***
SST Heatwave Maximum	-0.035
SST Heatwave Duration	-0.003
Storm Days (Waves)	-0.034**
Q2	-0.068
Q3	-0.045
Q4	-0.079
N	672
R^2	0.245
Adj. R^2	0.233
AIC	1138.396
BIC	1197.030
Log Likelihood	-556.198

Note: ^ $p < 0.1$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

8. Figures

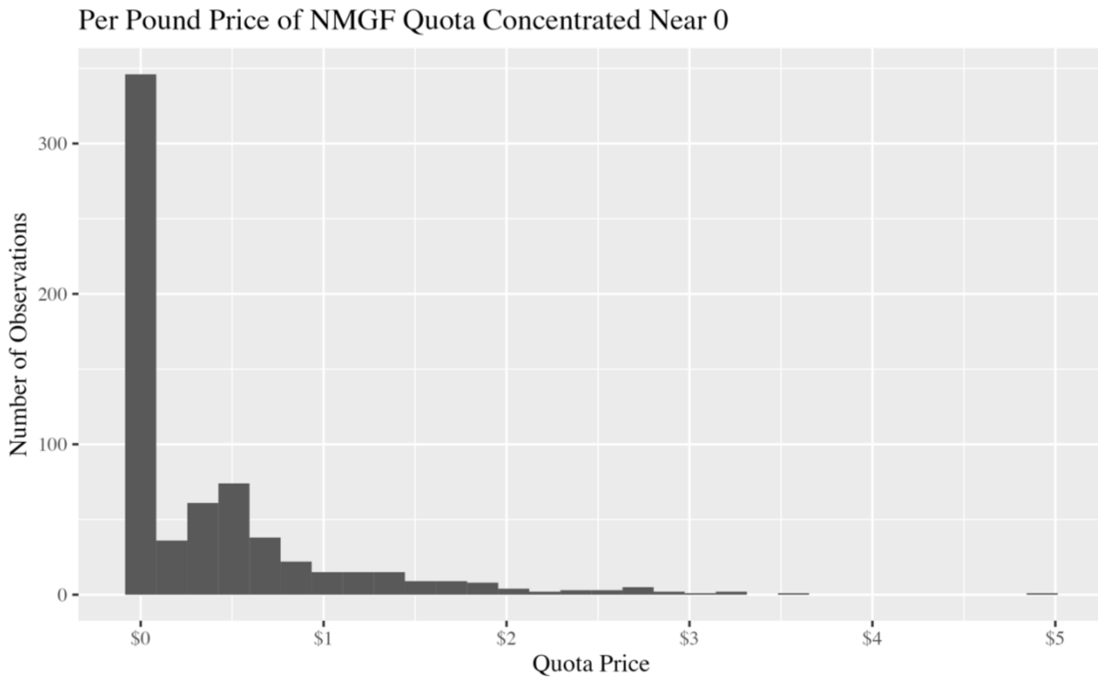

Figure 1: Distribution of Per Pound Price of NMGF Quota

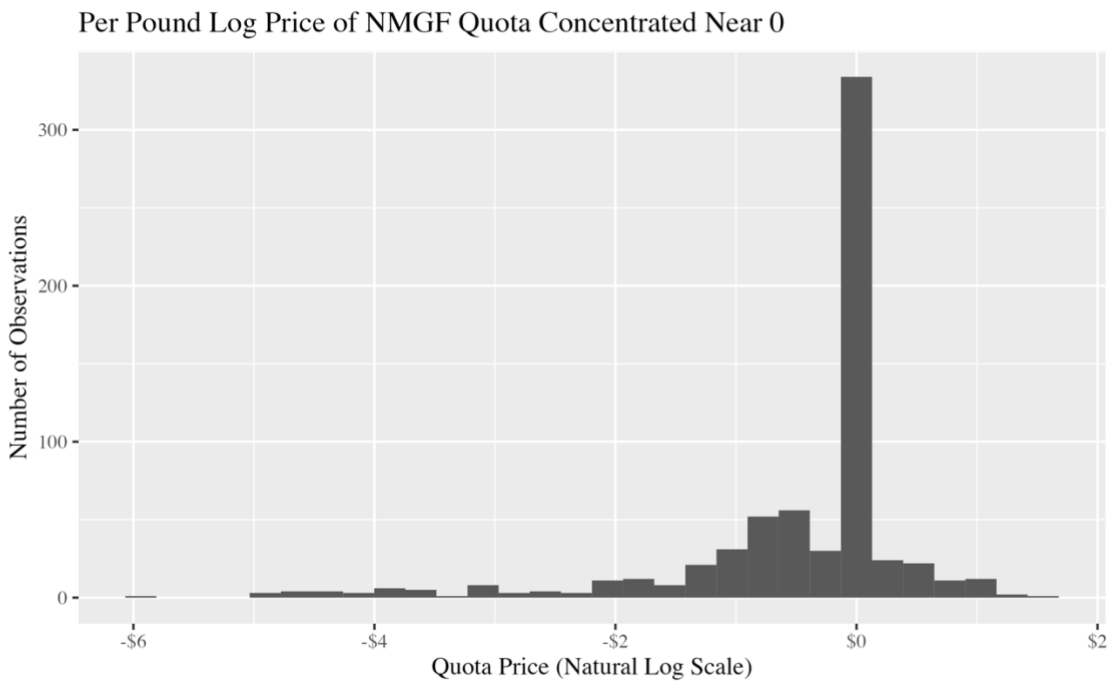

Figure 2: Distribution of Log Per Pound Price of NMGF Quota

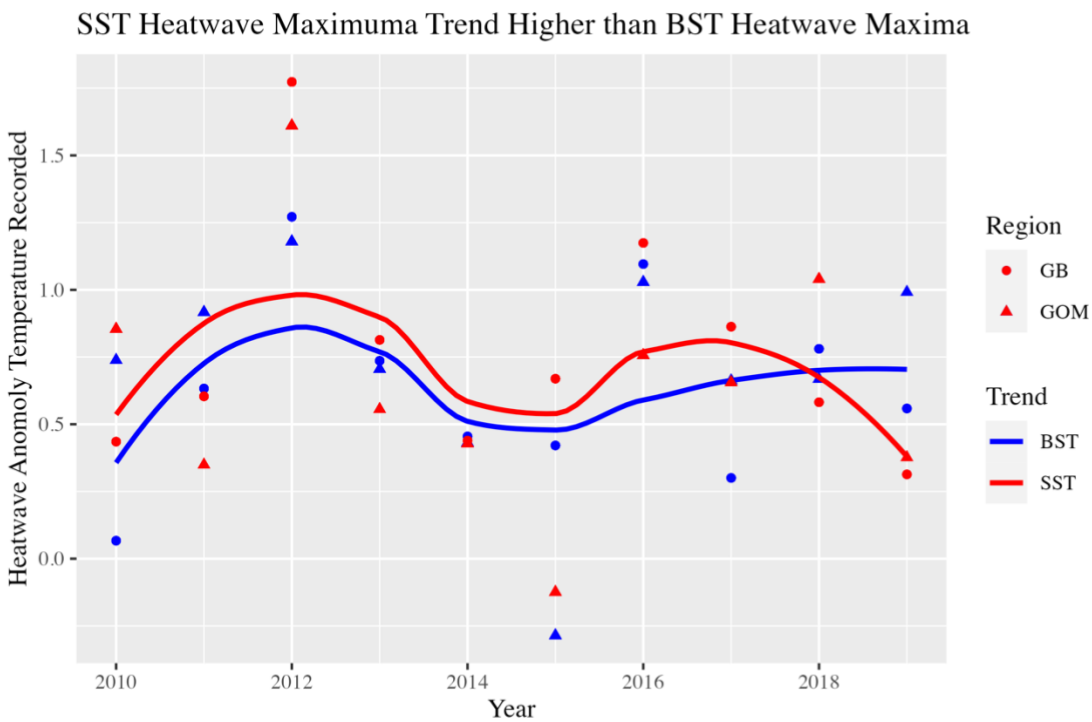

Figure 3: Maximum Heatwave Temperatures Reached

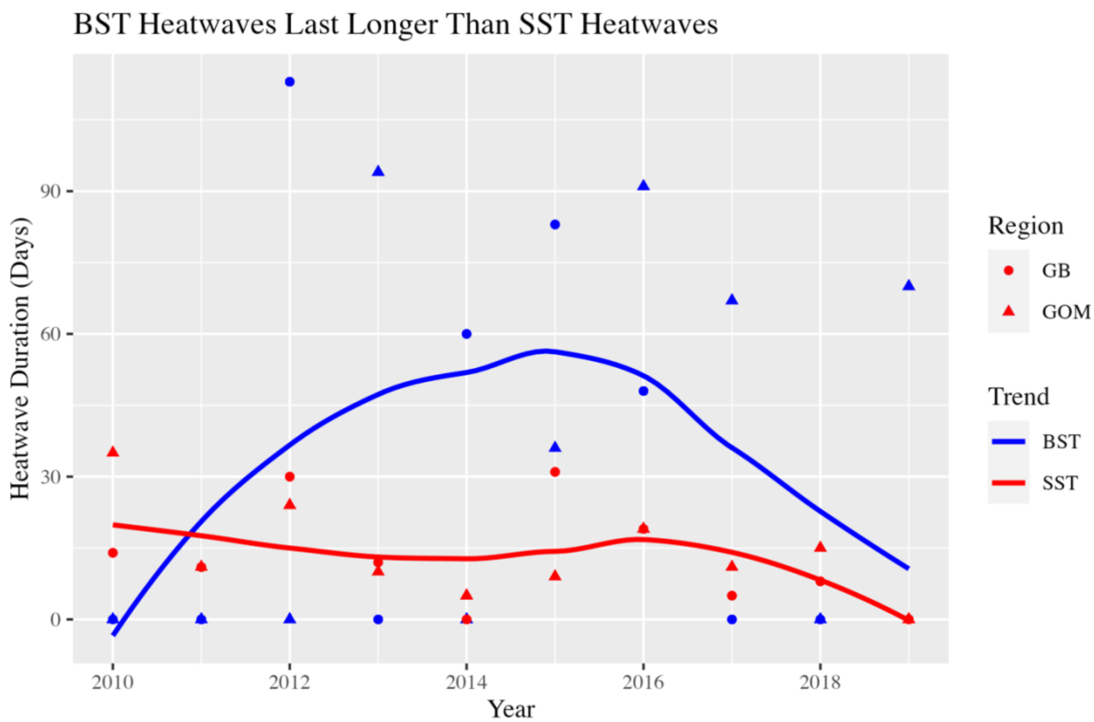

Figure 4: Duration of Heatwaves measured at BST and SST

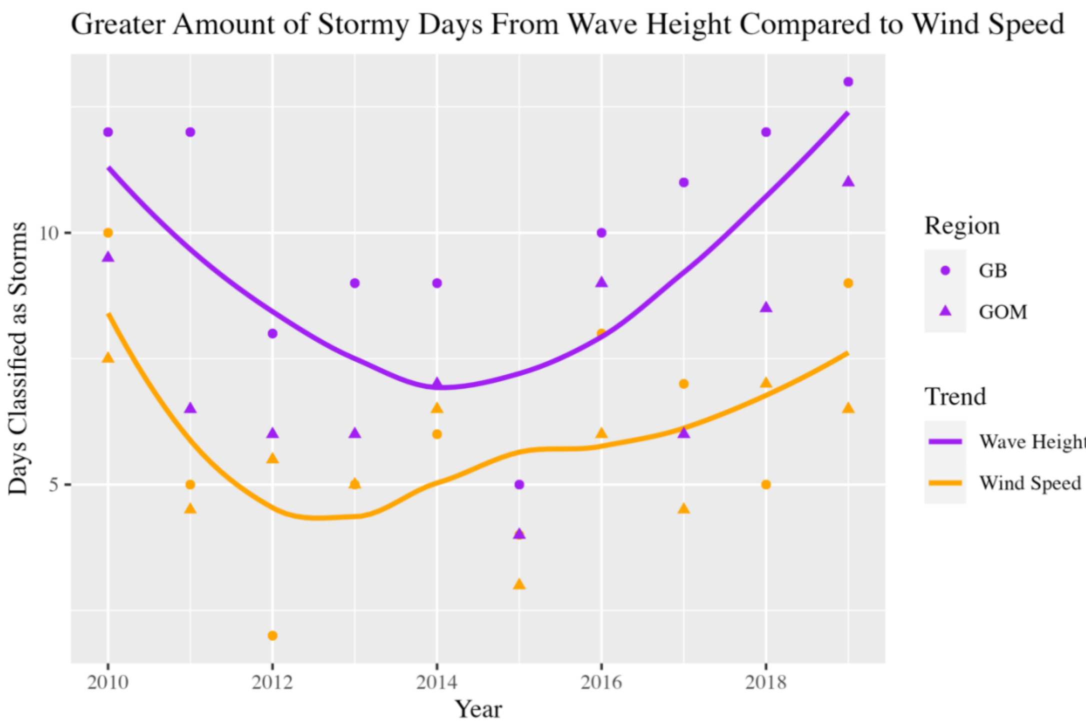

Figure 5: Storm Days Classified by Wave Height and Wind Speed