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Grower Risk and Community Perception: Impediments to Growing Maine's Aquaculture Industry

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GROWER RISK AND COMMUNITY PERCEPTION: IMPEDIMENTS TO GROWING MAINE'S AQUACULTURE INDUSTRY

By

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An Abstract of the Thesis Presented
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Maine has a long and proud history of working waterfronts and commercial fishing. However, in recent decades, aquaculture, or the harvesting or growing of aquatic life, has emerged as another player in the coastal economy. Globally, aquaculture is experiencing the fastest growth of any food sector in the world as it subsidizes floundering wild-capture fisheries (FAO, 2014). Maine and the rest of the United States have not yet participated in this growth, which has led stakeholders and policymakers like the National Oceanic and Atmospheric Administration (NOAA) to advocate for massive improvements to the sector by 2020 (NOAA, 2016). To ensure the possibility of sustainable growth, it is critical that the economic and social impediments are well understood. This thesis addresses two very different issues facing the aquaculture industry in Maine as it seeks to expand: the need for aquaculture growers to subsidize their income with off-farm labor and differences in community acceptance of aquaculture.

Chapter 2 examines the proclivity of oyster growers in New England to participate in off-farm labor. Off-farm labor is considered to be an important risk-hedging strategy, especially in an industry where crop insurance is not yet available. Data is collected from a 2016 mixed-mode survey conducted by the University of Maine's School of Economics across all oyster growers in Maine and Massachusetts (Scuderi & Chen, 2017). We explore how the growers' personal,

social, and business characteristics influence the likelihood of participating more or less in off-farm income generating activities. In addition, we borrow from a broad literature of agricultural off-farm labor supply studies to develop a framework for analyzing the off-farm labor decision specifically for aquaculture-based industries. The results indicate that a grower's age, education, gender, business size, and experience all play an important role in determining participation in income generating activities on and off-farm. We also find that learning and information sharing within the aquaculture industry can decrease off-farm labor participation. These results can offer insights for policymakers by providing information about what grower characteristics influence their ability to work on-farm.

Chapter 3 looks to examine community-level differences in acceptance of aquaculture across three coastal regions: Casco Bay, Damariscotta River region, and Penobscot Bay. Each region's economy is composed of many stakeholder groups who hold heterogenous preferences over aquaculture. These groups compete for limited coastal space such that changes in the coastal landscape can change the distribution of winners and losers. We build off the work of Evans et al. (2017) that uses hedonic price analysis to look at the impacts of small changes in aquaculture production on the coastal landscape. This work is extended by acknowledging that some policymakers and stakeholders are interested in growing Maine's aquaculture production in a nonmarginal fashion, a problem that requires a new set of tools to fully understand. A pure-characteristics equilibrium sorting model is utilized to investigate how observed large-scale changes in marine aquaculture might impact housing markets. A dataset composed of all coastal household transactions between 2012 and 2014 is used to investigate how coastal homeowners perceive aquaculture. Results show that relative changes in community price are induced when the utilization of coastal space changes. However, these results are muddied by an endogenous relationship between aquaculture and commercial fishing activities.

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CHAPTER 1

INTRODUCTION

1.1. Introduction

Aquaculture is playing a role in changing Maine's coastal landscape. Aquaculture producing activities can provide economic opportunities to communities who have traditionally relied on commercial fishing, especially for those fisheries that have been negatively affected by climate change and decades of overfishing. Aquaculture has become an increasingly important source of seafood protein throughout the world and the benefits of expanding marine aquaculture production have not been lost on U.S. policymakers. The National Oceanic and Atmospheric Administration (NOAA) has called for a 50% increase in aquaculture production by 2020, a call that has resonated with many U.S. policymakers and stakeholders. This sentiment has been echoed by policymakers and stakeholders within the State of Maine who hope the local industry can participate in this rapidly expanding global market. Unfortunately, these benefits have not been fully realized because of a complex set of relationships between other coastal resource users and aquaculture growers as well as the economic volatility inherent to operating small aquaculture operations. By examining both of these inhibitions to industry growth, this research provides a comprehensive overview of the challenges facing the expansion of Maine's aquaculture industry from a social science perspective.

1.2. Purpose of research

This research identifies two very different problems that need to be considered if aquaculture industries in Maine are to develop sustainably. This work hopes to help guide that process in several ways. First, we hope that Maine's stakeholders and policymakers find the results of this research helpful and informative when considering how to help growers weather an uncertain and sometimes tumultuous landscape. While we refrain from making any explicit policy recommendations, results may be informative to the policymaking process. The findings of these studies add nuance to the economic complexities that are woven into Maine's coastal communities. Second, we hope this research adds to each study's respective body of economic literature. Specifically, Chapter 2 contributes to the off-farm labor literature by expanding on the existing empirical framework to cater to aquaculture in the United States. Chapter 3 contributes to the equilibrium sorting literature by highlighting several of the concerns that surround this newer modeling technique. In particular, this research empirically demonstrates the sensitivity of the model in response to misspecification. Third, we intended for the findings of this thesis to contribute to the goals of SEANET by adding to the understanding of the sustainable ecological system (SES) framework through which we are trying to understand the challenge that face aquaculture in Maine.

1.3. Thesis outline

The following chapters will be presented as follows. Chapter 2 presents a study that explores off-farm labor decisions of oyster growers in New England. This section uses data collected in a 2016 survey and focuses on the marginal effects of demographics, business characteristics, climate factors, and information sharing. Chapter 3 employs a pure characteristics equilibrium sorting model to extend upon work conducted by Evans et al. (2017). This chapter explores the impact on communities of nonmarginal changes in aquaculture production across three regions of coastal Maine. It also serves to demonstrate some potential challenges facing a class of econometric seeking validation within the literature examine the valuation of nonmarket goods. Chapter 4 concludes the thesis with broader takeaways and recommended future work that builds upon the research presented here.

CHAPTER 2

OFF-FARM EMPLOYMENT IN AQUACULTURE: A CASE STUDY OF NEW ENGLAND'S OYSTER GROWERS

2.1. Introduction

Aquaculture is the farming of aquatic organisms such as finfish, shellfish, or plants in both fresh and marine waters. Globally, aquaculture production has experienced rapid growth over the last decade and now matches wild harvest in volume produced (FAO, 2016). Between 2000 and 2012, aquaculture was the fastest growing food sector in the world, growing at a rate of approximately 6.2% annually (FAO, 2014). One need not look past the global production trends over the last 20 years to see how important aquaculture is becoming as a source of seafood protein (FAO, 2014). In fact, aquaculture has surpassed wild-capture fisheries in volume produced and is expected to make up approximately 66% of all seafood production by 2030 (FAO, 2013). The causes of this exponential growth are two-fold. First, demand for seafood has continued to expand as the global population increases. Second, wild-capture fisheries are experiencing stagnation in productivity due largely to decades of overfishing which has placed many important fisheries on the brink of collapse, or worse, has already caused a collapse (Pauly et al, 2002). This combination of growing demand and declining natural supply has placed aquaculture at the forefront when considering alternative seafood sources.

If aquaculture is to continue to grow successfully, it is important that the inhibitions to growth are well understood. Aquaculture production is inherently susceptible to all kinds of risks, be they environmental, social, or market-based. As a result, growers utilize a variety of methods to mitigate their own risk. By analyzing different types of risks and the associated hedging strategies, policymakers in areas with expanding aquaculture industries will be better prepared to meet the needs of growers and thereby improve the health and sustainability of the industry. Off-farm labor employment of aquaculture growers is one such strategy that needs to be explored.

This study makes multiple contributions to the literature. First, this chapter addresses a prominent gap in the literature; off-farm activity in the aquaculture industry has not been studied at any length. Second, we develop an analytical framework to assess the off-farm labor supply in New England's oyster market, which would also be applicable to other aquaculture industries. Third, empirical analysis demonstrates evidence that a number of factors, including education, gender, age, and experience all play an important role in determining off-farm labor activity in the oyster industry. Finally, we examine the importance of access to information in off-farm labor decisions, which, as far as we know, has yet to be applied to aquaculture.

There is a robust literature on the topic of off-farm labor in agricultural markets, which has also expanded to include wild-capture fisheries (Mohd et al., 1993). Off-farm activities are playing an increasingly important role in sustainable development and poverty reduction, especially in rural areas (FAO 1998). Farmers have been shown to seek off-farm labor as a means to diversify employment and as a result stabilize income (Man and Sadiya, 2009; Schultz, 1990). However, there is an implicit tradeoff between on-farm and off-farm income as off-farm activities take effort away from on-farm activities. This has been shown empirically by Goodwin and Mishra (2004) who find a statistically significant inverse relationship between on-farm efficiency and off-farm labor supply. Farmers are also assumed to be risk averse, which has been confirmed through a number of empirical exercises (Mishra & Goodwin, 1997). While there is a sizable body of literature addressing off-farm labor in its traditional context of farming, there is a dearth of literature surrounding aquaculture growers' off-farm labor decisions. Given the growing impact and importance of aquaculture in the United States and around the world, we look to develop an analytical framework to understand off-farm labor participation in aquaculture industries.

This study adapts the traditional off-farm model to develop a new framework for analyzing off-farm labor across aquaculture markets in the United States. A new framework must include elements that are consistent between agriculture and aquaculture as well as elements that pervade specifically across aquaculture industries, while also considering regional and local market idiosyncrasies. There are several advantages to applying parts of an established structural framework to aquaculture's off farm labor problem, rather than creating a new framework. There are common covariates found ubiquitously throughout the literature, whose relationship with the off-farm labor decision is well tested such that casual relationships may be inferred from the models. Additionally, direction and significance of parameters that are commonly estimated can act as an informal check on our adapted framework. The danger lies in the assumption that farmers behave the same way and are subject to the same risks as aquaculture growers. We will do our best to carefully examine this assumption. Aquaculture growers and agricultural farmers in New England both face substantial capital investment barriers, operate in more rural areas on seasonal production cycles, and experience high levels of risk due to environmental factors (i.e. adverse weather changing climate, and disease). We are also aware of the differences between these two markets. Aquaculture markets, particularly in the United States, often cater to higher-end buyers. Mariculture is spatially constrained to coastal areas and farming is more prevalent in the nation's interior. Most importantly, these industries are regulated differently such that farmers have other forms of risk mitigation tools like crop insurance where growers do not and may be more reliant on off-farm labor (Beach & Viator, 2008). While these differences may alter the level of demand for off-farm labor (farmers in the region may participate less because they have larger palette of risk mitigation strategies), off-farm labor participation may well be partly determined by similar factors.

Using a mixed-mode survey, information is collected on the variables that capture exogenous market shocks and demand for off-farm labor. In addition, this study explores the impact of information sharing, which has been overlooked when evaluating off-farm labor participation decisions. Zero-inflated count models are used to produce parameter estimates. The aptly named zero-inflated models are able to evaluate datasets that have excessive observations of zeros. Though it is rarely adopted in the off-farm labor literature, it is a suitable tool to analyze the quantity of off-farm labor (in hours), which many growers choose not to supply.

We deploy our analytic framework to analyze the New England oyster market, which is an ideal subject of study for understanding off-farm labor mechanisms in aquaculture industries. For one, aquaculture in New England is relatively advanced when compared to most other parts of the country and the world that are just beginning to develop their own aquaculture industries. New England has a long history of growing well-known species like Atlantic salmon as well as a number of high-end shellfish like oysters. There are comparatively sound regulatory institutions and procedures in the market, and well-established information-sharing networks in place between growers and related institutions like professional associations, universities, and private research firms. Thus, we expect the results found in this study to apply to many regions that are looking to build healthy aquaculture markets. That is, because New England's oyster market is more developed than most aquaculture markets in the U.S., it is likely that growers in our sample are better suited to handle risks than the average grower in the country such that the results reported in this paper could apply more broadly than if we were to analyze a less developed market. This, coupled with the heterogeneity in business size, workforce socio-demographics, and climate allows us to gain a richer understanding of what drives variability in off-farm labor participation. Furthermore, the composition and largely rural setting of the industry may also allow for a higher degree of generalizability because few aquaculture hotspots are truly urban. In short, New England's oyster industry is a prime subject of study. The methods and findings of this paper will be important as aquaculture markets in the United States develop. By assessing the motives behind off-farm labor decisions in this market, this work allow policymakers to create better-informed policy related to the development of other aquaculture industries.

We consider heterogeneous composition and sizable economic impact to be two qualities that make the New England oyster industry an ideal subject to study. In 2013, there were more than 1500 leases, licenses and permits for place-based aquaculture of shellfish in New England. These leases were responsible for a production value that was estimated to be between $45 and $50 million (Lapointe, 2013). We focus on the states of Maine and Massachusetts where oyster aquaculture is primarily based. In 2014, Maine's aquaculture sector alone generated approximately $73.4 million in total economic impact with Eastern oysters accounting for the third largest revenue by species, behind Atlantic salmon and blue mussels. Additionally, the industry in Maine is responsible for 571 jobs and $25.7 million in labor income (Cole et al., 2017). In Massachusetts, Augusto and Holmes (2015) reported that the output value of the shellfish industry is estimated to be $25.4 million per year, while the industry contributes $45.5 million after value added considerations. Their study also found the industry in Massachusetts was responsible for creating 900 jobs and over $20 million in labor income. Across New England, oysters generate the most revenue of all shellfish and are by far the most valuable shellfish produced. New England oyster production accounts for a significant portion of the $173 million dollar oyster industry in the United States (NOAA, 2016).

What's more, oyster aquaculture in New England is growing, just like many aquaculture industries across the nation. Increasing demand for high quality shellfish has led to favorable market prices, which has encouraged the continued expansion of New England's oyster market over the past decade (Lapointe, 2013). The success of the market has led to new entrants, increasing volume produced and number of businesses over the last decade. In Maine, nearly 50% of oyster growing businesses started their operations in 2012 or later (Cole et al., 2017). It is also important to note that the vast majority of businesses that participate in oyster farming in New England are small businesses, with annual revenues below $500,000. In Maine, over 80% of businesses fall below the $750,000 annual revenue mark and are categorized as "small business" by the U.S. Small Business Administration rule (Cole et al. 2017). Similarly, Augusto and Holmes (2015) found that 94% of Massachusetts-based shellfish growing businesses took in annual revenues at or below $500,000. Because so many of these businesses are small, and there can be high seasonal volatility in earnings, many oyster growers may look to stabilize and subsidize their on-farm income with off-farm income.

This study also looks to explain how information sharing among growers and institutions impacts participation in off-farm labor, in part because there has been little work done to this end. Growers with access to more information may be more able to combat some of the environmental risks with which we are concerned because they will privy to the latest and greatest growing techniques. One study done by Johny et al. (2017) finds that the presence of strong intra-village social networks in Kerala, India can increase the impacts of household characteristics like education on off-farm labor participation. Another study conducted by VanWey and Vithayathil (2013) finds evidence that farm-level social networks in the Brazilian Amazon help facilitate an information-sharing network that increases the ability and reduces the risks for farmers who are seeking to participate in off-farm work. We are interested in the information and knowledge sharing components that these past studies explored. Rather than perform a full network analysis however, we are interested in how the number of contacts within the industry influences off-farm hours worked. This study also differs substantially from the settings of past studies in that, so far as we know, it is the first to examine the influence of knowledge and information sharing in a developed country with better and more institutionalized pathways for communication (Sevilla, 2013; Pratiwi & Suzuki, 2017).

The rest of the paper is outlined as follows. We discuss the construction of our analytic framework and our choice of economic model, which borrows from the off-farm labor literature in agricultural economics. We then discuss the data collection and analysis, followed by empirical results. We conclude by highlighting the significant findings of this work, and by recommending this paper as a template for empirical analysis of off-farm labor across aquaculture industries in the United States.

2.2. Analytical framework

It is held that farming families in the U.S. and other developed countries hold multiple jobs as a strategy for diversifying income and by extension, lowering income uncertainty (Huffman & El-Osta, 1997). The analytic frameworks applied to rural markets have evolved over the last several decades. In this chapter, we add additional structure to adapt a conventional off-farm labor framework (Mishra & Goodwin, 1997) to fit New England's oyster market. This study experiments with both discrete choice and count models to examine the relationship between off-farm labor hours per week and a suite of explanatory variables, some of which originate in off-farm labor literature and others that are introduced. Off-farm labor studies conducted within agricultural markets have found a number of factors that consistently and significantly influence off-farm labor decisions. Farm experience, income, farm size, age, number of dependents, level of education, health status, and distance to an urban center are a few of the right-hand side variables that are typically included to help explain variance in participation (Lass & Gempesaw, 1992; Sumner, 1982; Huffman & Lange, 1989; Ma & Mu, 2017). Apart from being integral to the model, the inclusion of variables found across agriculture off-farm labor studies can add validity to this chapter's findings if they agree in significance and direction. Business experience and size are expected to have an inverse relationship with off-farm labor participation, while education, number of children, distance to urban area, and age are expected to have a positive relationship.

Models are crafted to be regionally-specific by including local demand-side variables, spatially sensitive environmental factors, and state-specific information sharing features. We begin by using two classes of multivariate binary response models; the probit and the logit. These simple models will help us answer our first research question: what variables influence the binary choice of whether or not survey respondents choose to participate in off-farm labor in a coastal New England setting. Both models share an underlying form and differ only in the assumptions the econometrician makes regarding the distribution of the unknown errors (the random utility component). The logit model adopts a type I extreme value distribution of errors and its choice probabilities can be represented as:

$$\Pr(r_i \neq 0|\boldsymbol{X_i}) = \frac{\exp{(\beta \boldsymbol{X_i})}}{1 + \exp{(\beta \boldsymbol{X_i})}}$$

where the right-hand side denotes a logistic cumulative density function (CDF). Alternatively, the probit model which adopts a normal distribution of the errors can be seen as:

$$\Pr(r_i \neq 0|\boldsymbol{X_i}) = \int_{-\infty}^{X_i\beta} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(\beta \boldsymbol{X_i})^2}{2}\right)$$

where right-hand side is the standard normal CDF. In both cases, r_i is the likelihood that oyster grower *i* participates in off-farm labor.

While these models provide rudimentary insights into how the independent variables influence the binary choice decision, they do not provide information on the magnitude to which respondents participate in off-farm labor following their decision to participate. A more colorful understanding of the off-farm labor decision can be painted if we take advantage of the considerable and nonbinary variation in the dependent variable. Therefore, a more sophisticated econometric model is needed to explore our second research question: what are the factors that influence the number of off-farm labor hours worked?

We consider two count model specifications, the Poisson and the negative binomial, to better understand the relative size and significance of the relationship between off-farm labor and the factors that drive participation. These models are remarkably similar, differing only in the treatment of the dispersion of the data. If the overdispersion parameter (α) is equal to zero, meaning the equidispersion assumption of the data holds such that the variance and the mean are the same, then the two models are identical. We chose to experiment with both count model types for the sake of comparison, despite clear signs overdispersion within the data (the unconditional mean divided by the unconditional variance is approximately 25). The Poisson and negative binomial model can be loosely expressed as:

$$\Pr\,(H_i|\boldsymbol{x_i}, \varepsilon_i) = \exp\,(\alpha + \boldsymbol{X}_i'\beta + \varepsilon_i)$$

where:

- i refers to the i-th oyster grower
- H_i is the number of weekly off-farm labor hours performed by individual i
- $\boldsymbol{X_i}$ is a (1 x k) vector of explanatory variable inputs
- β is a (k x 1) vector of parameters to be estimated
- α is the overdispersion parameter
- ε_i is the randomly distributed error

The standard count models may start to address our second research question, but they ignore the excessive level of zero responses in the dependent variable (hours per week spent on off-farm labor). This issue is addressed by estimating a zero-inflated Poisson (ZIP) model and the more flexible zero-inflated negative binomial- Type 2 (ZINB) model. The data lends itself to these zero-inflated estimations as it contains an excess of zero responses (205 out of 423 observations), which could cause the standard Poisson or negative binomial regression models to predict the dependent variable poorly. A histogram detailing the frequency distribution of off-farm labor hours per week can be found in Figure A.1. By separating the count data into zero and non-zero groups, zero-inflated models may be better suited to predict off-farm labor provided by growers. This separation acknowledges that there is more than one process that could cause a grower to not participate in off-farm labor. A standard negative binomial or Poisson regression would not distinguish between different possible processes. The first group is referred to as the "certain zero" group, which is composed of growers who the model predicts would never participate in off-farm labor conditioned on the vector of regressors $(\boldsymbol{X_i})$. The second group is comprised of growers that could either participate or not participate. A grower's group is determined by a logit model that predicts whether or not that grower would participate in off-farm labor and a negative binomial model is used to model the second group only ($h_i > 0$). The same process applies to the zero-inflated Poisson regression, which differs only in the value of its overdispersion parameter. The discrete density function of the ZIP model can be expressed as:

$$\Pr(H_i = h_i) = \begin{cases} \omega_i + (1-\omega_i)\, exp(-\lambda_i), & h_i = 0 \\ (1-\omega_i) exp(-\lambda_i) \lambda^{h_i}/h_i!, & h_i > 0 \end{cases}$$

where:

- λ_i is both the conditional mean and conditional variance of the distribution
- ω_i is the zero-inflation probability

The corresponding logistic link function can be written generally as:

$$\pi_i = \frac{\lambda_i}{1+\lambda_i}$$

Much like the ZIP, the ZINB probability function can be expressed as:

$$\Pr(H_i = h_i) = \begin{cases} \omega_i + (1-\omega_i)(1+\alpha\lambda_i)^{-1/\alpha}, & h_i = 0 \\ (1-\omega_i)\dfrac{\Gamma(h_i+\alpha^{-1})}{y_i!\,\Gamma(\alpha^{-1})}\left(\dfrac{\alpha^{-1}}{\alpha^{-1}+\lambda_i}\right)^{\alpha^{-1}}\left(\dfrac{\lambda_i}{\alpha^{-1}+\lambda_i}\right)^{{y_i}^{h_i}}, & h_i > 0 \end{cases}$$

To determine the preferred model, two tests are run. First, the Vuong test compares the zero-inflated models to their respective non-inflated models. Then, a likelihood ratio test determines if the overdispersion coefficient (α) equals zero. Likelihood ratio tests compare the Poisson model to the negative binomial model, and the ZIP to the ZINB. The combined results from these tests help us to select the model that best fits the data. We also conduct AIC and BIC test to compare parsimonious goodness-of-fit across models.

2.3. Data

We collect information of covariates that are often considered in the off-farm labor studies (Mishra and Goodwin 1997; Goodwin and Mishra 2004; Woldeyohanes et al. 2016; Xie et al. 2018) and also covariates that are unique to aquaculture. The regressors are grouped into five categories excluding fixed effects: 1) Socio-demographic variables, 2) Business/Production variables, 3) Exogenous climate variables, 4) Information-sharing variable, and 5) Demand-side variables. To capture variation in businesses, this study considers years of growing experience, species diversification, and uses the number of oysters hauled annually to capture size of business. Household demographic information including age, education, number of dependents, gender, and marital status are also included in model. We use community-level income and population density information collected from the 2014 American Community Survey to capture the availability of off-farm labor opportunities in a community. Additionally, the distance of each grower from a town center with a population of 10,000 or more is calculated in ArcGIS. Note that the inclusion of supply-side variables like municipal-level unemployment rates, population density, and access to urban amenities are important in controlling for endogeneity in off-farm income. Exogenous environmental factors like annual precipitation and water temperature, which capture dynamic climate effects and can have a substantial impact on a business's yield, are also included. Moreover, we include a variable that measures the number of information sources a grower uses within the industry. Growers were asked to include up to eight in-state industry contacts as part of our survey. They were also asked to include contact occupation, the type of information shared, and to rank them in order of importance. This study uses the number of contacts reported operates as a proxy for the amount of information a grower has access to. Finally, annual fixed-effects variables are used to control for temporal variation from year to year, which should account for larger shocks to the market.

This paper uses primary data collected in a 2016 survey (Scuderi & Chen, 2018). Economic analyses of the aquaculture industry often employ surveys to obtain microdata. The survey was sent to all aquaculture growers in the New England states. Several growers and extension experts were selected in a survey pretest procedure to help inform the design and delivery of the survey. Given limited resources, Scuderi and Chen opted for a mixed mode approach, where oyster growers in Maine were mailed a paper copy of the survey, growers in Massachusetts were both mailed a paper copy of the survey and emailed an electronic copy, and growers in New Hampshire were only emailed an electronic copy. Each grower who received a paper copy was offered a $1 cash incentive. Two follow-up surveys were sent to growers who had not yet responded, and a $20 cash incentive was offered to those who completed the survey and returned it. In 2016, there were a total of 530 oyster aquaculture businesses in New England according to the leasing records provided by the state governments: 387 in Massachusetts, 126 in Maine, and 17 in New Hampshire. The survey was sent to every one of them. The authors had 172 surveys returned, with a final response rate of approximately 32%. Approximately half (205 out of 423 observations) of the growers participated in off-farm labor, with a mean participation of 15.3 hours per week.

The survey asked for information spanning three years (2013-2015) and a number of topic groups including:

- Production Methods and Species Produced
- Farming Inputs, Outputs, and Capital Investments
- Knowledge and Information sources
- Demographic and Business Information

Our analyses include data from the production methods, farming inputs and outputs, species diversity, aquaculture experience, number of information sources, off-farm labor, and demographic information sections.

Due to concerns expressed by growers during pretesting, the survey did not collect information on income of each grower. Additionally, while the survey captures many supply-side variables for off-farm labor, it does not provide us with demand-side information. To address these issues, the survey data is subsidized with information from multiple sources including the 2014 American Community Survey (ACS). We collect data on median income, unemployment, and population density at a ZIP code spatial level. This data is matched with each grower's business ZIP code. These measures act as a proxy for supply-side potency; that is, income, unemployment, and population density provide the econometrician with a baseline understanding of off-farm labor opportunities. Table A.1. shows the summary statistics and descriptions of the relevant variables.

The survey data is further supported with information on annual precipitation and ocean surface temperatures to evaluate whether changes in climate would affect grower's labor supply. Precipitation data was gathered from Geographic.org, which holds a catalog of land-based weather station data. Data from 78 weather stations across upper New England is collected and ArcGIS is used to match each address to the closest weather station to produce an approximation of annual rainfall for each oyster growing area. Water temperature data was collected from 7 buoys in the Gulf of Maine and around Cape Cod and accessed through NOAA's National Centers for Environmental Information. The same process was used to match oyster-growing sites to their respective water temperatures, noting that the effect of climate is being increasingly recognized in the off-farm labor supply literature (Uddin et al., 2014; Okonya et al., 2013; Ahearn et al., 2006). Annual precipitation is one method that has been used to capture climatic variance across farms (Chen & Vuong, 2018; Ahmed & Goodwin 2016). For land-based agriculture, temperature anomalies are another climate identifier. So, while water temperature is not a variable that appears in traditional off-farm labor literature, it appears here to capture some of the same climatic effects in aquaculture.

2.4. Empirical analysis and discussion

For each of our economic models; probit, logit, Poisson, negative binomial, zero-inflated negative binomial, and zero-inflated Poisson, the model is loosely specified as:

$$Pr(OFL_i = y_i) = F(\hat{\beta}X_i)$$

where OFL_i is the off-farm labor decision (either binary or in hours per week), X_i is the set of explanatory variables and $\hat{\beta}$ denotes the coefficient estimates (see Table A.1. for a complete list of regressors). Each model's results are useful, however the zero-inflated negative binomial model is found to be the preferred model in terms of equidispersion and goodness-of-fit. We find that results across all models are comparable, with direction and significance changing little between them. Additionally, the variables borrowed from agricultural off-farm labor literature agree in direction. Grower experience, business size, age, gender, and education all hold the expected signs and are statistically significant.

Results for the logit and probit models can be found in Table A.2. and can be interpreted qualitatively by their sign and statistical significance. However, they will not be discussed at length because they do not address the degree to which each explanatory variable influences off-farm labor decisions.

In the preferred model, there are significant results in the first four categories of our regressors: 1) Socio-demographic variables, 2) Business/Production variables, 3) Exogenous climate variables, and 4) an information-sharing variable. Interestingly, the variables relevant to the demand of off-farm labor such as population density, distance to an urban center, and unemployment rate, do not have a significant impact on participation. Other demand-side controls, such as labor force participation rates may want to be considered in future analysis.

The zero-inflated negative binomial model can offer deep insights into how growers weight their off-farm labor decisions. Coefficients in the positive finds group represent the difference in the log of the count induced by a marginal change in an independent variable. This can be interpreted directly as a percentage change in the conditional mean of weekly off-farm labor hours supplied, scaled by the variable whose effects are being estimated. These coefficients are presented in positive finds section of Table A.3.

The interpretation of the logit selection is slightly different. Increasing a variable with a positive coefficient would raise the likelihood of a grower being selected into the "certain zero" group by a factor of the exponent of the coefficient. Likewise, increasing a variable with a negative coefficient would lower the likelihood of a grower being selected into the "certain zero" group by a factor of the exponent of the coefficient.

Results for the Poisson, negative binomial, ZIP, and ZINB regressions can also be found in Table A.3. There are some substantive differences between the two zero-inflated models indicating that the equidispersion assumption may not hold (the overdispersion parameter estimate is 0.288). The ZIP model does not correctly account for overdispersed observations and as a result, some parameters are identified as significant in the ZIP model but not the ZINB. We use likelihood ratio tests to demonstrate the superiority of the ZINB model over the ZIP model. Additionally, Vuong tests examine how appropriate the use of the zero-inflated models is when compared to the standard negative binomial and Poisson regressions. In both cases, the results are highly significant and thus the zero-inflated models are, unsurprisingly, a better fit (Table A.5.). A comparison of AIC and BIC statistics across our models reinforce these results from Table A.3.

The sensitivity of the models is explored in other ways. We experiment with panel fixed-effects models but found that they were too costly in degrees of freedom. Also, attempts are made to address some of the concerns that come with applying zero-inflated models to our off-farm labor data. In Figure A.1. there are two peaks, one at zero hours and one at approximately 40 hours weekly. This could suggest the presence of three distinct classes: those who work full-time on-farm, those who work nearly full-time, and those who only a few hours a week on-farm. The same analysis is done on the subset of our data where weekly off-farm labor hours worked were 40 or fewer. The results between our full model and partial model are strikingly similar and as such, they are not reported in this chapter. Rounding error could also explain the increased number of 40-hour responses and is a common problem found in count data. We do not control for rounding error in this chapter.

Results demonstrate that gender, experience, and education are heavily associated with off-farm labor participation. Having decided to take up off-farm income-generating activities, a grower who has one additional year of education is expected to participate in 3.38 additional hours of off-farm labor per week; a grower who has one additional year of experience is expected to participate in 0.69 fewer hours of off-farm labor per week; and a male grower is expected to participate in 27.58 additional hours of off-farm labor per week when compared to his female counter parts, *ceteris paribus*. If a grower is married or engaged, they are less likely to participate in off-farm labor all together. However, if they choose to participate (placed into the positive finds group) they are not expected to participate any more or less than their unmarried counterparts. We uncover a negative relationship between a grower's experience in oyster production and off-farm labor participation. A more experienced a grower is less likely to participate in off-farm labor, and even if she does participate, she is expected to participate for fewer hours per week. Likewise, growers that produce a larger volume of oysters are less likely to participate in off-farm labor, but even if they do participate, they will be expected to participate fewer hours per week. Furthermore, warmer water temperatures are found to be associated with more off-farm labor participation. Lastly, we find a significant and negative relationship between the number of contacts that growers collect information from and off-farm labor participation. A grower who is provided information by one additional contact decreases off-farm labor participation by approximately 1.71 hours weekly. A complete list of marginal effects can be found in Table A.4.

Interestingly, the number of dependents, which is often considered to be a very important covariate in off-farm labor models, has no significant impact on participation in these preliminary models. This could be due, in part, to the setting being studied. To iterate, off-farm labor models today are typically applied to small farms in developing countries that tend to have higher rates of poverty and fertility and lower rates of education. We posit that the low fertility rate (the most school-aged children reported in the survey was three) leads to low variation. This, paired with the relatively high-end nature of the market may explain the absence of influence usually associated with number of dependents.

The model unearths other surprising results. Namely, it can be seen that information-sharing has an inverse effect on off-farm labor compared with past studies in the literature. Grower's with more industry contacts are expected to participate less in off-farm activities, where other studies have found that it increases the likelihood of participation (VanWey & Vithayathil, 2013). This could be due in part to differences in approach and variable construction. However, it may also be because acquiring knowledge in highly developed markets of wealthier countries serve to make farming more lucrative and stable. In poorer countries with less developed industries, farmers use information channels to gain knowledge and receive opportunities to increase their income through off-farm activities. Additionally, we observe that the information-sharing systems in Maine and Massachusetts appear to behave in a similar way. When the information-sharing variable is interacted with a state-specific dummy variable, it is insignificant. While states have distinct information-sharing networks, we suspect they operate in a similar fashion. That is, in the cases of both Maine and Massachusetts, we would expect the more connected growers to participate less in off-farm labor. Finally, we see a small but statistically significant bump in off-farm labor participation in 2013.

2.5. Policy discussion and conclusions

This study investigates the propensity for oyster growers to participate in off-farm labor. Off-farm labor is a strategy for limiting risk in an industry that has an underdeveloped set of risk mitigation tools. We look to shed light on an import and rapidly growing sector of food production –aquaculture – which has been, to this point, unintentionally overlooked in the off-farm labor literature. Information gathered in a 2016 survey was used to construct variables that represent a broad slate of potential decision-making forces. Both supply-side variables, like grower demographics and business size, and demand-side variables that influence off-farm work availability such as employment opportunities are considered in our analysis. We find off-farm labor participation among oyster growers in New England is motivated by a number of diverse drivers. This study indicates that grower demographic characteristics are important in explaining the off-farm labor decision process, with things like gender, level of education, and age all playing a role. Business and production variables play a part in off-farm labor decisions as well, with larger, more experienced growers participating less. Additionally, higher water temperatures lead some growers to participate more in off-farm labor which is likely due to higher risk and lower relative yields in production when water is relatively warm.

Perhaps of the most interest, the model demonstrates that having a more sources of information within the industry lowers off-farm labor participation. We posit that growers who have more connections to one another and to institutions that regulate oyster production are more likely to succeed for two possible reasons. The first explanation is that growers who have access to more information are better able to adapt to production shocks and are generally more efficient in their production.

A second explanation is that there might be a case where growers who are dependent on oyster growing as their primary source of income are more likely to seek out information than those who are not. This provides a unique opportunity for future research. Distinguishing between those who participate in off-farm labor because they have to versus those who participate because they want to will help us refine our policy recommendations. If the goal of policy is to make growing a more sustainable business endeavor, then policymakers should work to identify those who have no choice but to subsidize their income with off-farm labor, as opposed to hobbyists. Hobbyists are those who work primarily off-farm without intention of becoming fulltime growers. For this group, minimizing off-farm participation may not be the goal as it is not being used as a risk mitigation strategy. There may be a third group of growers who participate in off-farm labor still. Commercial fishers and lobster fishers are using aquaculture as a way to subsidize their primary income. This is due in part to the volatility of several New England fisheries, who are seeing moratoriums or cap and trade policies limit a fisher's ability to work and thus earn a living (MAC, n.d.). Aquaculture is a way for this group to diversify income. This group has a unique relationship with off-farm labor as they may seek out more sources of income within the aquaculture industry, but still use commercial fishing or lobstering as their primary income. Understanding how knowledge and information effects each of these groups differently will provide policymakers with more pointed recommendations with which they can design policy. Nevertheless, by broadly identifying the inverse relationship between off-farm labor and the amount of information growers have access to, we are confident in making general policy recommendations. Namely, by broadening access to information for growers who need off-farm labor to earn a living, those growers will be better able to sustain themselves within the industry. If policymakers and stakeholders improve information dissemination pathways such as industry meetings, regular newsletters on the latest technology and growing techniques, or workshops on growing technique, growers who are struggling to insulate themselves against downturns in production are adding another risk-hedging strategy to their arsenal.

Overall, the off-farm labor framework is well suited to study oyster aquaculture in New England, producing results that are consistent with intuition. While understanding the underpinnings of off-farm labor decisions among growers in New England is valuable in and of itself, much of the value of this chapter is the empirical structure this chapter contributes to understanding aquaculture industries more generally. First, we demonstrate that zero-inflated models are suitable for analyzing the off-farm labor phenomenon. Next, we show that the consideration of both supply and demand side variables may be important, as well as the inclusion of variables that capture the degree to which growers share information. This study can serve as a template in applying off-farm labor theory to aquaculture markets across the United States at a time when aquaculture is becoming increasingly important as a source of seafood. By examining the characteristics that motivate growers to choose to participate in off-farm labor, insights into areas in which policy may apply can be gained. If aquaculture in the United States is to continue to grow sustainably, it is critical that policymakers understand what causes growers to turn to these key risk-minimizing approaches. To conclude, we hope this chapter can help guide stakeholders, including policymakers, businesses and even consumers in developing aquaculture industries in an economically sustainable way.

CHAPTER 3

BEYOND MARGINAL IMPACTS: VALUING MAINE'S MARINE AQUACULTURE IN A RESIDENTIAL SORTING MODEL

3.1. Introduction

Global aquaculture production has experienced rapid growth over the last decade and has surpassed wild-capture fisheries in production by volume. This growth is expected to continue as global demand for seafood expands while wild-capture fishery production stagnates due to changing ocean conditions and rampant overfishing (FAO, 2016). The United States is poised to take advantage of this economic opportunity by expanding its aquaculture sector (Evans et al., 2017; Knapp, 2008; Valderrama & Anderson, 2008; Kite-Powell, Rubino & Morehead, 2013). In particular, we note the demand-side potency of the U.S. market. Ranking 16th globally, the United States is a relatively minor producer of aquaculture, but is the world's leading seafood importer (NOAA, 2018). The U.S. imports over 80 percent of its seafood and in 2017, imported \$21.5 billion, which was more than any year prior (NOAA, 2017). To counteract this staggering deficit, policymakers in the United States have set lofty expansionary goals for marine aquaculture. For example, in 2016 the National Oceanic and Atmospheric Administration (NOAA) established a target of increasing U.S. marine aquaculture production up to 50% by 2020 (NOAA, 2016). While some of this projected growth is expected to take place in areas without established aquaculture industries, it is likely that much of the new production will be generated through the expansion of existing industries.

Maine, which has a long history of aquaculture production and thousands of miles of coastline, is one of the places where aquaculture has expanded and where more growth should be expected. Maine's stakeholders and policymakers alike have suggested that growing the state's aquaculture industry could serve as a mechanism to subsidize depleted wild-capture fisheries and to support rural coastal communities that struggle economically (Lapointe, 2013; Knapp & Rubino, 2016; Sustainable Ecological Aquaculture Network, 2016). In 2014, Maine's aquaculture industry was estimated to have a direct economic impact of $73.4 million (Cole et al., 2017), producing on as little as 0.03 percent of Maine's public waters (Department of Marine Resources (DMR), 2016). This is a marked increase from a similar study conducted in 2007 which uncovered a direct economic impact of only $30 million (Morse & Pietrack, 2009). Maine's economic and geographic situation make it an ideal candidate for expanding marine aquaculture production to satisfy domestic demand-side needs.

However, the interest that many have in expanding coastal aquaculture has not gone unimpeded. Knapp and Rubino (2016) and Evans et al. (2017) highlight how expanding the presence of aquaculture production areas disrupts other coastal resource users. By introducing new aquaculture production into coastal systems, the relative provision of coastal resources is altered, and the resulting redistribution leads to an increase in utility for some resource users and decrease in utility for others. Coastal homeowners, recreationists and commercial marine fishers are just a few of the parties concerned that the negative externalities created through expanding aquaculture will *not* be counteracted by the positive externalities. Still, compromise may be possible. Communities across coastal Maine hold diverse preferences for marine aquaculture. By revealing the idiosyncratic preferences held by different communities through the behavior of homebuyers, we may be able to identify aquaculture siting possibilities that have a net benefit for coastal resource users.

To correctly estimate the impacts of a quickly changing seascape on different groups of coastal resource users, it is imperative we utilize the correct tools for analysis. Traditional methods, such as the hedonic price model may be ineffective when extra-marginal changes are considered. In this chapter, we turn to a class of model called the equilibrium sorting model, which combines properties of market equilibrium and assumptions regarding households' locational choices to estimate community-level WTP for changes in coastal aquaculture production. This chapter uncovers community-level willingness-to-pay for aquaculture production as a means of understanding the heterogeneity in preferences for marine space along the coast of Maine.

The willingness-to-pay estimates we present in this study are of a different order of magnitude than previous studies and are inconsistent with prior expectations. Sensitivity tests unearth possible explanations, namely the resources that populate Maine's coastline may be endogenous to one another. Therefore, aquaculture, as it has been defined in this study, may be capturing some of the effects of other amenities occupying coastal space. Still, the relative sensitivity of communities to changes in the use of that coastal space is determined.

3.2. Background

Maine has over 100 aquaculture growers and grower organizations who produce an impressive diversity of species across more than 300 leases (Cole et al., 2017). Atlantic salmon, oysters, clams, scallops, and sea vegetables like kelp encompass much of what is produced in the state. It is important to note however that the majority of Maine's aquaculture revenue is generated by harvesting Atlantic Salmon, which are not examined in this thesis. We focus primarily on the growth of shellfish, specifically oysters, clams, scallops. Leases are licensed and managed jointly between the Maine Department of Marine Resources (DMR) and the Maine Department of Environmental Protection (DEP). The state offers three possible license choices: Standard leases, limited purpose leases (LPAs), and experimental leases. These leases differ substantially in the allowances they offer growers (e.g. maximum acreage, lease duration, species allowed, and procurement difficulty). Maine is somewhat unique in its licensing and siting process. There are no predefined marine growing zones like the ones found in Chesapeake Bay, Maryland (Maryland Natural Resource Code §4-11A-05, 2015), and across other countries like the United Kingdom, Australia, and Japan. Instead, there are unique processes growers must go through to obtain each of the three lease types. To obtain a standard lease, growers propose lease areas to the DMR; the DMR is then charged with holding three highly political lease hearings and public comment periods. Coastal landowners are given notice when a proposed standard or experimental lease is within 1,000 feet of their property. Non-landowners are notified by newspapers and through the DMR website. Interested parties are invited to provide testimony which can either support or oppose the proposed lease. Interestingly, testimony is required to be objective in nature such that changes in viewscape and the impact on property values are not considered in the final licensing decision. The final licensing decision falls to the DMR commissioner, who must consider how the proposed lease site may interfere with landowners' land access, shipping lanes, fisher ability to operate, protected or endangered plants and animals, or public use within 1,000 feet of government managed beaches, parks, docks, and land (DMR, n.d.).

The LPA leasing process differs from the process of standard leases detailed above. Note that LPAs are responsible for a very small amount of the total aquaculture production area but make up most of the recent growth. These leases are small (400 square feet or less) and must be renewed on an annual basis. Landowners are only notified if the LPA is within 300ft of their property. Additionally, there is no scoping session or public hearing process where the public can voice concerns over proposed LPAs. This can introduce additional tensions between aquaculture growers and other coastal resource users. Statewide, LPAs occupy only five acres of land. However, the inability of homeowners and other coastal resource users to participate in the process further muddies the waters.

Experimental leases are the third and most uncommon mode of lease. These leases are provided on a one-time basis, such that they may not be renewed. Experimental leases may operate for one to three years and can be up to ten acres in size. They hold the same 1000 feet notification requirement that standard leases do, but the hearing and scoping process is dependent on the lease. The scoping session comes at the discretion of the commissioner of the DMR, while the public hearing will be initiated if there are more than five comments in the public comment period or if the DMR commissioner finds a hearing necessary (MRSA, 2013).

This unconventional licensing process leads to curious spatial patterns in lease sites. Aquaculture leases are distributed along the entire coastline but there is significant clustering in certain areas like finfish in the Downeast portion of the state and shellfish in the Damariscotta River region which further complicates the relationship between other riparian resource users and aquaculture growers. Because of the clustering patterns of lease sites around the state, there may be reason to suspect that aquaculture perceptions across each of the three study regions may vary significantly from community to community.

Work has already been done to better understand the relationship between resource users and their perceptions of marine aquaculture. Numerous studies have found evidence that conflict arises in coastal areas where aquaculture is being introduced (Mazur & Curtis, 2008; Shafer et al., 2010; McGinnis & Collins, 2013). Critics of aquaculture development often cite environmental impacts, human health implications, and social tensions that arise from the introduction of aquaculture as concerns. This research is primarily interested in how aquaculture production is perceived by coastal homeowners, we consider social tensions and influence on viewscape as the leading mechanisms in generating variation in household preferences. In their study, Shafer et al. (2010) find that New Zealand residents who are in close proximity to mariculture have higher degrees of sensitivity to development as well as more negative perceptions of aquaculture, despite their recognition of the positive economic effects that are associated with said development. While qualitative research exploring resident perceptions of aquaculture has been valuable, quantitative analysis is needed as well. Unfortunately, attempts to empirically value changes in marine aquaculture production are rare. As such, this research builds off research compiled by Evans et al. (2017), where coastal regions were demonstrated empirically to have heterogeneity in preferences for aquaculture. The authors examine the willingness-to-pay (WTP) of coastal homeowners for a marginal expansion of mariculture on three coastal regions in Maine: Casco Bay, Penobscot Bay and the Damariscotta River region. Utilizing a semiflexible form hedonic pricing model, Evans et al. (2017) unearth distinct regional preferences. Specifically, Casco Bay and Penobscot Bay both yield a negative WTP for marginal increases in aquaculture production, although the estimates for Casco Bay were statistically insignificant. This indicates that, in general, Penobscot Bay views aquaculture as a disamenity. Conversely, the Damariscotta River region is found to have a positive and significant WTP. The relationship each region has with aquaculture could be used to explain these differing results. Casco Bay is the southernmost region in the study area and the urban center of the state. Its waterfront has traditionally been used for recreation, fishing, and shipping. Penobscot Bay is the northernmost region in the study area and is composed largely of towns with tourist-driven economies. Lastly, the Damariscotta region sits between Penobscot and Casco bays, and is unique in its dependence on working waterfronts and its history of promoting shellfish aquaculture activity. The results found by Evans et al. (2017) are meaningful when considering a marginal increase in the space used for aquaculture production. However, policymakers and stakeholders are advocating for large-scale, or non-marginal changes to the coastal landscape. In this thesis, we consider the problem of large changes in the utilization of coastal space and estimate WTP at a community-level using the correct tool for analysis: the equilibrium sorting model.

3.3. Literature review

3.3.1. Difficulties in valuing environmental amenities

Economists have been developing hedonic models, like the one used by Evans et al. (2017), to describe willingness-to-pay for a range of products and amenities since Rosen (1974) pioneered the technique. By exploiting housing and labor markets in particular, economists are able to measure WTP by observing implicit prices across differentiated products. Hedonic methods have been particularly popular for those engaging in nonmarket valuation of environmental amenities. The hedonic property model emerged as the go-to model for environmental economists using revealed preference data and it is now generally accepted that housing price differentials are reflective of preferences for an entire slate of environmental goods and services (Freeman et al., 1993). Unfortunately, assumptions that underpin hedonic property models limit their use as an effective policy tool. The models are effective in producing marginal willingness-to-pay (MWTP) estimates in the so-called "first-stage" bid function. However, environmental policy frequently involves non-marginal, discrete changes like closing of a mill, building a nuclear reactor, or enacting a new air quality policy (Sieg et al, 2004). The "second-stage" hedonic bid function is capable of producing WTP estimates for these large or discrete changes, but in practice this proves to be econometrically taxing and requires using a reduced form of the hedonic price function, which makes identification challenging (Freeman et al., 1993).

Additionally, hedonic property models can examine how changes in an environmental amenity impact the housing market but have little to say about how it will affect other "goods" over which consumers hold preferences (e.g. cost of living, school quality, availability of urban amenities). While a partial equilibrium framework is suitable for assessing impacts around the margin, they fail to capture discrete changes, largely because of the ripple effect that large environmental changes produce in other markets. It is intuitive then that we utilize a general equilibrium framework to account for these intermarket interactions.

Equilibrium sorting models have been suggested in response to these shortcomings. Sorting theory was born out of Charles Tiebout's realization that people "vote with their feet" (Tiebout, 1956). Tiebout recognized that because there is heterogeneity in household preferences for nonmarket goods, there could be migrational effects when an area experiences a discrete change in those goods. "Sorting" then is a metaphor for the process of households migrating between and settling in communities in accordance with their income and preferences. In other words, by observing the movement of households when they are faced with amenity changes, the researcher can gain insights into their preferences for those amenities. Within equilibrium sorting models, the researcher can observe households that are heterogeneous in both income and preferences sorting themselves across communities that differ in both relative cost of housing and community-level provisions of environmental, urban, and other locally available public goods. Equilibrium sorting models elicit household heterogeneity by estimating parameters for preferences based on observed data and using properties of market equilibria. This process is not dissimilar from the hedonic and discrete-choice models found in industrial organization (IO) literature on differentiated product markets (Kuminoff et al., 2010). Where the hedonic pricing approach finds an equilibrium outcome, usually around the margin in a partial equilibrium setting, the equilibrium sorting approach instead characterizes the sorting process and finds an equilibrium in the general equilibrium setting. A model of sorting can be developed by exploring the interactions between household preferences, community costs, and variation in locational amenities. Within that model, an equilibrium can be achieved when the demand for housing equals the available supply of housing in each community, and distributions of housing types and their prices are determined (Freeman, 2014).

Additionally, equilibrium sorting models can be an incredibly useful policy tool and have traditionally been used in evaluating the impact of environmental effects. By adding structure and manufacturing household preference estimates, the econometrician is able to estimate community-level WTP for non-marginal changes of an amenity in a general equilibrium framework. The theoretical framework of the model has been demonstrated empirically and results have been consistent with theory (Smith et al., 2004).

3.3.2. The pure-characteristics equilibrium sorting model

Sorting models have fallen into three distinct frameworks: the random utility sorting (RU) model, the calibrated sorting (CS) model, and the pure characteristics equilibrium sorting (PC) model. We focus on the third. These models vary in their assumptions about the choice process, expression of household preferences, and use of instrumental variables in estimation (Kuminoff et al., 2013a). RU models and CS models are sometimes called horizontal sorting models in line with the industrial organization (IO) literature (Waterson, 1989). Horizontal sorting models hold that a household's preferences for an amenity is horizontally differentiated such that there is no implicit rank ordering of quality. This means that for any given amenity, households can disagree about which communities are the are the closest substitutes, which leads to greater variety of substitution options. RU models define the choice set as the home conditioned on the job of the primary earner of the household which recognizes the relationship between community choice and workplace, where CS model's choice set focuses on the tradeoffs between school quality and price of housing. Additionally, RU models use the attributes of substitute amenities which are calculated as a function of housing characteristics within a community and the exogenous amenities within all other communities to create the price-quality instrument. CS models, on the other hand, model the production function of the endogenous amenity (Kuminoff et al., 2013a). Table B.1. describes the major differences across the three types of sorting models.

The PC sorting model used in this chapter separates itself from the others primarily in that it considers amenities to be vertically differentiated. Vertical sorting models assume all households in the model hold preferences over the same amenities and hold the same weight for each of those preferences. These assumptions imply that households all agree on a rank ordering of communities (Evans, 2011). The PC sorting model is different from the CS and RU primarily in its treatment of amenity differentiation. The vertical differentiation of amenities allows households to unanimously rank communities by price, which acts as the instrument used to address endogeneity between community-specific amenities and households' community choice.

All sorting models impose high levels of structure on the data and utilize properties of market equilibrium to evaluate discrete changes in environmental and other nonmarket amenities. The PC model, developed by Epple and Sieg (1999), PC models are distinct in their treatment of agent choice which requires households to make a two-stage decision. First, households who hold preferences over a series of amenities must choose the community that maximizes their utility given that community's provision of those location-specific amenities. Then, conditional on the community choice, those same households must decide how much housing and how much of the private good (numeraire) they wish to consume. The treatment of housing within the PC equilibrium sorting model is distinct in that households are asked to consume a continuous amount of indexed housing units which are equally priced and homogenous (Kuminoff et al., 2013a). Model parameters are estimated using a one-stage generalized method of moments (GMM) estimator. Parameter estimates are used to simulate a large number of households with heterogeneous preferences and income, which can then be used to predict how these households might react to discrete change. In this case, we use real world changes in amenities such as school quality, water quality, aquaculture, and others that will be described in the data section of this paper. By examining the change in distribution of households across the communities, it is relatively straightforward to estimate WTP. While we are interested in examining how observed changes in aquaculture and other amenities impact the housing market for validation purposes, a proposed strength of the equilibrium sorting model is its ability to *predict* how changes that have not yet been observed in amenities will impact housing markets. The remainder of this section details the model's upfront assumptions and the process by which it achieves equilibrium and produces WTP.

3.4. Theoretical framework

3.4.1. Model structure

In this chapter, we will follow their model and notation laid out in the Epple and Sieg's seminal paper (1999). The authors present a description of the model where there is an economy that consists of a continuous and finite spatial landscape of households, C, that are heterogeneous in their preferences for locally available goods, α, and in their income, y. These households reside in a landscape that is broken into J communities with fixed boundaries that need not be homogenous in size, shape, or population. These communities differ in price for homogenous units of housing p_j and their provision of these locally available goods, g_j, known in the literature as the "public good". Take note that the "public good" found in the equilibrium sorting literature is quite distinct and separate from the non-rivalrous and non-excludable public goods found in microeconomic literature. The public goods in this thesis are instead assumed to be community specific and typically include things like urban amenities, school quality, and environmental attributes. Now, in this landscape, households hold preferences over g_j, but also over a housing good, h, and composite of private goods known as the numeraire, n. The numeraire could include things like country clubs, private gyms, or marinas. Households are constrained by their income and are assumed to save nothing, spending all remaining income on the composite private good. A households' locational choices are assumed to be jointly determined by α and *y* and their joint distribution, *f*(α,*y*), is assumed to be continuous. This model assumes that communities differ only in the index set of characteristics that fall within the public good.

Recall the household location decision can be thought of as a two-step process where a household must first select the community which offers the preferred level of the public good. Conditional on that choice, the household then chooses the amount of housing and numeraire to consume. Since it is assumed that households can purchase as much housing as they desire (constrained by their income and indirectly by their preferences) at the market price in each community, the number of homogeneous housing units a household consumes becomes a function of the provision of the public good and the price of a community, as well as the household's preferences and income. A household's indirect utility can then be seen as:

$$V(\alpha, g, p, y) = U(\alpha, g, h(p, y, \alpha), y - p * h(g, p, \alpha, y), \alpha)$$

Given this specification, maximizing household utility becomes a matter of selecting the utility maximizing community, j, from communities $j = 1, \ldots, J$ conditional on income and community price.

$$j^* = \underset{j}{\operatorname{argmax}} \{V_j\}_{j=1}^{J}$$

where j^* is the community that maximizes household utility and V_j is the indirect utility a household receives from choosing community j. A sorting equilibrium is reached when every household is in its preferred community given income and prices where prices are endogenous to the household community choice. This is consistent with market clearing conditions that require aggregate demand for housing H^D to be equal to aggregate supply for housing H^S in community j at price p_j. This can be written as:

$$H_j^D(p_j) = H_j^S(p_j)$$

It may be helpful to consider a simple thought experiment. Imagine there are two communities that may differ in their shape, size, and population, as well as in their air quality. The community with better air quality (community 1) is more expensive to live in, which implicitly indicates that households in both communities agree that that community 1 is the community of higher rank. There is an implicit tradeoff between how much housing a household can purchase and the air quality of the community they live in. Households who hold stronger preferences over air quality will be more willing to sacrifice housing than those who hold weaker preferences. Additionally, households with looser income restraints will be more able to afford the pricier community. The intuition is that households will sort themselves based on their preferences for air quality and their income. As households who hold strong preferences and higher income move to community 1, its price will begin to rise. In response, households who hold weak preferences for air quality, or who have income restraints that require them to move will migrate to community 2. This process continues until no household would be better off by moving. By observing the migration of households and the resulting price changes in the communities, it is possible to assess the effect that air quality has on utility for each household.

3.4.2. Model conditions

PC equilibrium sorting models are highly-structured parametric models. As such, there are necessary conditions that are imposed on the model that allow the sorting process to occur. Ellickson (1971) was the first to derive restrictions used to induce sorting behavior. Westoff (1977) then provided a proof that a sorting equilibrium exists in a model given heterogeneity in household income. Westoff's work was extended by Epple, Filimon, and Romer (1984) and

Epple and Romer (1991) to include market clearing conditions. Epple and Platt (1998) further extend the model to account for heterogeneity in income, which led to the current characterization of three essential restrictions; stratification, boundary indifference, and ascending bundles, which are collectively known as the “single-crossing condition.” The following conditions are defined as follows:

1) *Stratification* -The stratification condition argues that households will sort themselves across communities continuously based on their joint distribution of taste and income. This can be represented algebraically as:

$$\left(y_{j-1}|\alpha\right) < \left(y_j|\alpha\right) < \left(y_{j+1}|\alpha\right) \ \textit{and} \ \left(\alpha_{j-1}|y\right) < \left(\alpha_j|y\right) < \left(\alpha_{j+1}|y\right)$$

That is, conditioned on taste (α), the income (y) of households in community $j-1$ will be less than that of households in community j, which in turn will be less than the income of households in community $j+1$ *and* conditioned on income (y), the tastes of households in community $j-1$ will be less than that of households in community j, which in turn will be less than the taste of households in community $j+1$. This assumption is critical to the rank ordering of communities by taste *and* income.

2) *Boundary indifference* – Boundary indifference allows there to be households with given taste and income that are indifferent between communities *j* and *j+1,* which are adjacent in relative price. This can be seen algebraically as:

$$\boldsymbol{V}\left(\alpha, \bar{g}_j, p_j, y\right) = \boldsymbol{V}\left(\alpha, \bar{g}_{j+1}, p_{j+1}, y\right)$$

It is intuitive that, given a continuous joint distribution of households (α, y) broken into discrete communities $j = 1, \dots, J$, that there will be some households who fall on the boundary between two communities that are adjacent in their rank. This is illustrated in

Figure B.1., where K_j denotes the boundaries on which households within the continuum may fall.

3) *Ascending Bundles* – Ascending bundles states that the structure of the model allows us to assume that the relative community price p_j and the relative provision of the public good g_j move together such that they can understood as synonymous to one another. The ascending bundle property is written as:

$$y_{j+1}(\alpha) > y_j(\alpha) \ \rightarrow \ p_{j+1} > p_j \ and \ g_{j+1} > g_j$$

The ascending bundles property allows the researcher to understand community quality, which is unobservable, through community price, which is observable.

Together, these assumptions imply that household indirect utility curves in the price-public good space (g, p) are monotonically increasing such that they cross only once. The properties of the single-crossing condition are essential to achieving a sorting equilibrium. Epple and Sieg (1999) these properties to develop community ranking instruments which are used in identification. The households' interpretation of single-crossing condition can be understood visually from Figure B.2. Households *a*, *b*, and *c* are sorted into communities C_1, C_2, and C_3 which are delimited by boundaries K_1 and K_2. Community C_1has the lowest quality and C_3 has the highest quality. Household *a* holds the lowest income but still sorts into the community of the highest quality because it holds the strongest preferences over the public good. Household *c* sorts into C_1 despite having the highest income because it holds the weakest preferences over the public good. A household's joint determination of community under the single-crossing condition can be understood mathematically as:

$$M(\alpha, g, p, y) = \left.\frac{dp_j}{dg_j}\right|_{V \, = \, \bar{V}} = -\frac{\partial V / \partial g_j}{\partial V / \partial p_j}$$

where $M(\alpha, g, p, y)$ is monotonically increasing in income conditional on taste $(y|\alpha)$and taste conditional on income $(\alpha|y)$. That is, a households' indirect utility is a function of the amenities provided by the community in which they live and the preferences that that household has over those amenities, as well as the price of housing in that community and the income of the household. By employing Roy's identity, M is conveniently decomposed into a two-piece Marshallian demand schedule:

$$\frac{1}{h(p_j, y)}\left[\frac{\partial V/\partial g_j}{\partial V/\partial p_j}\right]$$

where the first piece is the inverse housing demand and the second piece is the Marshallian virtual price for the public good. This means that, holding income constant, the price-per-unit of housing will be rising strictly in preferences for the public good relative to the private good (Kuminoff, 2013a). While the literature has not provided a formal proof of single-crossing condition achieving a sorting equilibrium, there have been numerous quantitative validations (Epple & Sieg, 1999; Epple et al., 2001; Smith et al., 2004; Kuminoff, 2009; Klaiber & Smith, 2010; Evans, 2011).

It is important to note that while the single-crossing condition is necessary to create a sorting equilibrium, it alone is not sufficient to ensure an equilibrium. Because the sorting landscape is composed of communities that are characterized by a vector of housing prices and a vector capturing the provision of the public good, it is also assumed that a sorting equilibrium can only be established once every household is consuming the optimal level of housing *h* and private goods *n* in optimal community *j*. To summarize, the single-crossing condition is necessary in facilitating a sorting equilibrium and is central to the estimation of the PC equilibrium sorting model.

3.4.3. Model parametrization and sorting

PC equilibrium sorting models take a robust theoretical structure and parameterize it, resulting in a complex structural equation model which has taken several different forms. The original model specification adopted a general Cobb-Douglas functional form (Epple & Platt, 1998). However, today's model utilizes the constant elasticity-of-substitution (CES) form, which has several useful properties. By adopting the CES structure, the model's indirect utility equation separating it into two distinct parts:

$$\boldsymbol{V}(\alpha, \bar{g}_j, p_j, y) \ = \left\{\alpha g^{\rho} + \left[exp\left(\frac{y^{1-\gamma}-1}{1-\gamma}\right) exp\left(-\frac{\beta p^{\omega+1}-1}{1+\omega}\right)\right]^{\rho}\right\}^{\frac{1}{\rho}}$$

where ρ is a measure of substitution between housing and the provision of the public good, γ is income elasticity, ω is price elasticity, and β is a scaling parameter on housing demand. The first term (αg^{ρ}) can be roughly interpreted as the utility provided from the public good. The second term in the equation is the utility derived from the contribution of private goods, which depends on income and housing.

The CES structure has useful properties apart from separating the private and public good components of the indirect utility function. If $\rho < 0$, the CES function satisfies the single-crossing condition. Additionally, the structure of the model allows us to easily derive housing demand, which takes a convenient Cobb-Douglas form (by following Roy's identity):

$$h(p_j, y) = \beta p_j^{\omega} y^{\gamma}$$

The introduction of the necessary conditions bundled within the single-cross condition induces sorting by allowing for the separation of household parameters and community characteristics,

$$M(\alpha, y) \equiv \underbrace{\ln(\alpha) - \rho\left(\frac{y^{1-\gamma} - 1}{1-\gamma}\right)}_{\text{Household Characteristics}} = \underbrace{\ln\left(\frac{Q_{j+1} - Q_j}{g_j^{\rho} - g_{j+1}^{\rho}}\right)}_{\text{Community Characteristics}} \equiv K_j$$

Q_j is a community-level provision of private goods that considers community price and the degree of substitution between the private and public goods such that:

$$Q_j = \exp - \left(\frac{\rho\left(\beta p_j^{\omega+1} - 1\right)}{\omega + 1}\right) \forall j = 1, \dots, J-1$$

As such, K_j can be thought of as a community characteristics index that is a function of both public goods, g_j^{ρ}, and private goods, Q_j, that occurs at the boundary of communities j and $j+1$. Notice how the boundary indifference property to is used to build K_j, which operates as a cutoff mechanism to households as they sort across the landscape. $M(\alpha, y)$ represents those households which are characterized by their taste and income and are indifferent between communities j and j+1. Household $M(\alpha, y)$ is a simulated household whose taste and income parameters are drawn from a joint distribution that is developed using observed housing data. In essence, $M(\alpha, y)$ operates as a household preference index.

Given community cutoff points, K_j, and households $M(\alpha, y)$, the sorting process becomes quite simple. If $M(\alpha, y) > K_j$, the household will prefer community *j+1* over community *j*. Conversely, if $M(\alpha, y) < K_j$, the household will prefer community *j* over *j*+1. Because of the ascending bundles property, households with a higher $M(\alpha, y)$ will prefer communities that offer a larger provision of the public good despite the higher cost of housing. The sorting process is recursive. The community with the lowest price (*j=1*), and by extension the lowest provision of the public good, is filled first. This is followed by community *j=2* and each consecutive community up to community *J*. Each community is filled and markets clear when housing demand in each community equals housing supply. Sorting is designed to capture an indifferent household's tradeoff between consuming more housing and numeraire with a lower provision of the public good, and consuming a higher provision of the public good but having to pay more for each unit of housing.

3.4.4. Model estimation

The empirical model was estimated using MATLAB. We follow the estimation procedures developed by Epple and Sieg (1999) and refined by Sieg et al. (2004). Estimation relies on a generalized method of moments (GMM) approach that takes advantage of the high level of structure built into the model. In their seminal paper, Epple and Sieg propose a two-stage estimator to generate point estimates of parameters. In the first stage, the community-level income distribution is expressed as a function of parameters that are included in the model's structure. The second stage of estimation relies on simulated moment conditions which are built from instrumental variables that are consistent with community price rankings. Essentially, the simulated moments are stacked such that there exists a system of equations that is being estimated simultaneously. This can be thought of as a series of root problems whose purpose is to find the parameters that minimize the distance between the observed and predicted data. The parameters estimated by the GMM process, along with observed household data are used to model the sorting process from which regional, community, and simulated household WTP can be calculated.

Sieg (2004) propose an alternative one-stage estimator using simulated GMM that is employed in this chapter. In addition to income quantiles and the implied public good, housing expenditures are also used to formulate moment conditions. Seven moment conditions are constructed from housing expenditure quantiles (25^{th}, 50^{th}, 75^{th}), income quantiles (25^{th}, 50^{th}, 75^{th}), and the implied level of the public good provision. While smaller quantile delineations can be used to improve the precision of the model's estimations, typically this requires larger amounts of data than are available to the researcher.

The first set of moment conditions that minimize the difference between 25th, 50th, and 75th predicted and observed log income percentiles can be seen as:

$$lny_j^O(q) = lny_j^P(q) = 0$$

Superscripts *O* and *P* represent observed and predicted log income quantiles, and q represents the q^{th} quantile. The second group of moment conditions seek to minimize the difference between observed and predicted log housing expenditures. Quantiles are taken by aggregating housing expenditures at the community-level and determining the cost per unit price. Using the housing demand equation ($h\left(p_j, y\right) = \beta p_j^{\omega} y^{\gamma}$) and information on the normalized prices for housing in each community, we derive the stack of moment conditions:

$$lnE_j^O(q) - \ln(\beta) - (\omega + 1)lnp_j - \gamma lny_j^P(q) = 0$$

The final moment condition, a linear approximation of the provision of the public good, can be seen as:

$$\tilde{g}_j - \vartheta X_j = \varepsilon_j$$

Here, X_j indicates the community-specific attributes that are observable to both the household and the econometrician, and ε_j designates those community-specific attributes that are observable to the household but not the econometrician. It is assumed that ε_j does not impact that rank ordering of communities and that it does not vary systematically with X_j. This is a critical assumption, as the econometrician cannot observe the entire public good. Within the model, $\tilde{g}_j$ is a function that outlines the recursive algorithm used in the sorting process. Each community's public good is, in part, a function of the previous community's public good, leaving g_1 as a parameter within the model. $\tilde{g}_j$ is approximated using community cutoff points, K_j, and structural parameters, such that:

$$\tilde{g}_j = \left\{ \tilde{g}_1^{\rho} - \sum_{i=2}^{j} (Q_i - Q_{i-1}) \exp\left(-K_{i-1}\right) \right\}^{\frac{1}{\rho}} \forall\, j = 2, \dots, J$$

This study follows the methods of Kuminoff (2009) to construct the instruments necessary for exogenous sorting. Given that community price and community quality move together as per the ascending bundles property, Kuminoff recommends using Chebychev polynomial functions on community price rankings to generate instrumental variables. Instruments are needed in estimation because of the potential for correlation between community-level fixed-effects, and equilibrium prices and the public good. This implies that unobserved amenities do not systematically influence the sorting process. That is, the unobserved component of the public good may affect the level of income in each community, it must not change the rank ordering of communities by income. This highlights the importance of capturing the major forces that influence locational decisions within the public good. While the entire public good cannot be directly observed, by observing household locational choices, community prices and amenities, and population shares, the implicit public good can be measured.

3.4.5. Willingness-to-pay estimation

The PC equilibrium sorting model is capable of producing general equilibrium Hicksian WTP estimates given multiple and simultaneous changes to the community-level goods in the model. One of the advantages of using equilibrium sorting methods over other partial equilibrium methods is that households are able to make new locational choices given a large change in their environment. Hicksian WTP in a partial equilibrium context would be defined as:

$$\boldsymbol{V}\left(\alpha, \tilde{g}_j, p_j, y - WTP_{PE}\right) = \boldsymbol{V}\left(\alpha, g_j, p_j, y\right)$$

, which clearly limits the choice of the household to community *j* given the change in public good from g_j to $\tilde{g}_j$. The general equilibrium framework of the PC equilibrium sorting models includes no such restriction. Households are able to respond to changes in locally available goods over which they hold preferences such that:

$$\boldsymbol{V}(\alpha, \tilde{g}_k, \tilde{p}_k, y - WTP_{GE}) = \boldsymbol{V}(\alpha, g_j, p_j, y)$$

Here, k denotes the household's new community choice, and $\tilde{g}_k$and $\tilde{p}_k$ are the corresponding levels of the new community's public good and price. Willingness-to-pay of each simulated household is estimated, and can then be aggregated at a community-level by mean, median, or other moments of interests.

3.4.6. The counterfactual equilibria

In order to calculate WTP for a discrete change in an amenity, a counterfactual equilibrium must be computed. Equilibrium sorting models are distinct in their ability to estimate the WTP for any number of counterfactual equilibria. First, estimated parameters are applied to our observed data to generate a baseline landscape of simulated households. From here, the impact of a counterfactual change in any or all of the public goods is computed. Again, we follow the methods laid out by Sieg et al. (2004). First, a large number of households are simulated by being drawn randomly from the distribution, $f(\alpha, y)$. These simulated households are sorted across communities given the observed levels of community prices, the various public goods, and population shares. Housing supply is the mechanism through which the model can close, such that sorting is complete once housing demand is equal to housing supply in each community. The housing supply function is written by Sieg et al. (2004) as:

$$H_j^S = l_j p_j^{\tau}$$

where l_j is a community-specific constant controlling for size and other fixed components, and τ is the constant supply elasticity. Kuminoff et al. (2013) acknowledge that housing supply is typically held as constant or calibrated using constant supply elasticity, but more work needs to be done to characterize the supply-side within equilibrium sorting models.

Given changes to the level of the public good offered by the community to each of the simulated households, new equilibrium prices can be computed. To do so, a system of nonlinear equations given by the market-clearing conditions for each community $j = 1, \dots, J$ must be solved. The process starts with an initial guess at the price of the lowest price-ranked community, and community housing markets clear sequentially following the sorting process outlined earlier, ending with the highest price-ranked community $J - 1$. The initial guess is adjusted, and the process repeated until the J^{th} market clears.

3.5. Limitations of the empirical model

The equilibrium sorting approach circumvents a number of critical issues within the hedonic literature and makes several important improvements on other nonmarket valuation techniques, but it too has limitations. Limitations come in many forms and can stem from the data entering the model, the choices the researcher has to make in specifying the model, or be a product of the model itself. These models impose high levels of structure based on assumptions that are built into the model and assumptions made by the researcher. As such, model validation and sensitivity tests are imperative to widening the acceptance of these models (Keane, 2010; Kuminoff et al., 2013b). There have been efforts to validate sorting models, including an unpublished dissertation (Evans, 2011) which conducted both an inside and an outside sample validation of the model, but more work needs to be done.

This section aims to call attention to some of the challenges that face the equilibrium sorting models and make suggestions for improvements. For instance, the PC equilibrium sorting framework requires that households unanimously agree upon the ranking of communities by their provision of locally available amenities. It is reasonable and prudent to assume that households do not in fact behave this way. While efforts have been made to relax this assumption (Epple, Peress, & Sieg, 2010), it remains a vulnerability of the model.

A second important limitation to this model lies in the assumption that the community's initial provision of the public good is exogenous to choices made by home buyers. That is, when a household chooses a community, the level of each component of public good is unaffected by the migration of the household to that community. In reality, it is reasonable to expect a level of endogeneity between a household's community choice and the level of public goods provided by that community since it is the households within the community that make decisions on the provision of certain public goods. However, some goods are more endogenous than others, such as open space and school quality (Kuminoff et al., 2013). This issue may be unavoidable in this paper. The model requires us to assume that changes in the landscape between the baseline and counterfactual scenarios are caused by exogenous shocks. However, household participation in the aquaculture leasing process is inherently endogenous to the changes in the amenity.

A third and highly concerning component of any econometric endeavor is omitted variable bias (OVB). PC models are particularly susceptible to OVB because they lack an intercept and error term. In the model, the public good defines the entire universe of goods and services over which households hold preferences. By either including an amenity in the public good that in reality is not a part of the household choice, or by omitting an amenity that is a part of the household choice, the entire sorting process may be altered. Where other models, like a hedonic, may simply overestimate or underestimate the impact of a variable has explaining the variation in price and expand their random error term, PC models are fundamentally changing the process through which we attain an equilibrium. The effects of the omitted variable are absorbed by other components of the public good such that WTP may be hugely inflated.

A fourth limitation of PC equilibrium sorting models in general is that they allow for frictionless or costless movement when the landscape experiences an exogenous shock. In other words, every household has an *equal* ability to move. This can lead to an overestimation the migration of households in their response, which is a problem the models in this paper experience. In reality, we expect there to be a relatively high cost of moving. Households derive utility from unobservable, and in some cases intangible goods that never enter our model. Things like attachment to a house, neighborhood relations, and access to idiosyncratic amenities that fall outside the scope of the public good all play a role in the real-world household choice. A cost of movement is one way of approximating the effects of these unobservable factors. To this end, efforts have been made. Kuminoff (2009) demonstrates how assumptions underlying costless movement influence welfare measures. Ferreira (2010) and Epple, Romano and Sieg (2012) include moving costs in their estimates and find that its inclusion has a significant impact on marginal willingness-to-pay (MWTP) estimates.

A final limitation is the model's sensitivity to the definition of the community. The community is the smallest unit of analysis in the model, but more importantly the community decision has consequences on both the sorting process and the initial parameter estimates (Kuminoff, 2009). We use elementary school districts, a popular choice in equilibrium sorting literature, as our unit of analysis. School districts are often chosen because school quality is an important element in informing the household locational choice. However, this leaves the model vulnerable to estimation error because much of the data that make up the public good, housing prices, and income levels are collected at municipal, census tract, and other special levels. Thus, when the data is interpolated to the desired spatial unit, extra degrees of measurement error are introduced. While the PC equilibrium sorting model is the correct tool for analysis, it is important to be aware of these limitations, particularly when considering policy implications.

3.6. Data

3.6.1. Housing data

As with other revealed preference approaches, equilibrium sorting models require large amounts of data in order to produce reasonable estimates and accurate predictions. This section will describe the data collection and manipulation process used to generate WTP. Table B.5. describes the summary statistics for all of the model's inputs.

We collect two primary datasets. The first dataset is comprised of transactions for single-family homes sold in Maine between January 1, 2012 and December 31, 2014. This data thoroughly details household characteristics as well as transaction price and date. This data was provided by the Maine Multiple Listing Service (MMLS), a private organization that provides information to realtors. Addresses were geocoded by the authors of Evans. et al (2017) by matching them to road files accessed through the Maine Office of GIS via the automatic match function. The addresses that remained unmatched were assigned locations manually using a best guess approximation via Google Maps. Taking the data geocoded by Evans et. al (2017), we conduct our own extensive cleaning. First, each home's structural characteristics and price are flagged for any obvious outliers (e.g. 100,000 square feet) or obvious errors (e.g. zero bedrooms or bathrooms). Next, all characteristics of each flagged home are cross-checked with publicly available data supplied by Zillow and Realtor.com. Observations that contained errors and could not be validated were dropped from our sample. Our final samples consisted of 6,112, 2,316, and 1,678 observations for the Casco Bay, Damariscotta River, and Penobscot Bay regions respectively. This data is used to generate community prices.

3.6.2. The first-stage hedonic

The aptly dubbed first-stage hedonic was originally proposed by Sieg et al. (2002) as a means of generating community prices. A hedonic fixed effects model allows us to generate an index of community prices (and quality) which is continuous in nature. The prices are indicative of differences in the provision of the public good across communities, as the hedonic price function serves to homogenize housing units within the model. The hedonic function is seen as:

$$\ln(r_{ij}) = \beta' S_{ijt} + \sum_j \delta_j C_{ij} + \sum_t \delta_t Y_{it} + \varepsilon_{ijt}$$

where S_{ijt} captures the structural characteristics of household *i* in community j, that is sold in year *t*. C_{ij} captures the community fixed effects and Y_{it} captures time fixed effects. The estimated parameter δ_j provides the community price indices. Note that r_{ij} is the renter's price, not a homeowner price of the household. This implies that gains from changes in home price are not given to the occupant of the household, but rather some other absent landlord entity. Typically, rental prices are derived interest rates on home loans and local property tax rates, as well as artificial maintenance rates, risk preferences, and depreciation of the home. We use a calibrating coefficient borrowed from Evans (2011) to generate renter prices, multiplying each household price by 0.136. We follow Evans (2011) because the author uses methods outlined by Porterba (1992) to calculate imputed rents (which are equivalent to annual housing expenditures), and because the resulting housing expenditure scalar is one of the most recent reported in the sorting literature. A complete list of dependent variables can be found in Table B.2. Additionally, results from the hedonic regressions can be found in Table B.3. Most of the parameter estimates carry the expected sign and are significant.

3.6.3. Income data

Recall that households are constrained by income within the sorting process. Income data is gathered from the American Community Survey (ACS) at the Census tract-level and then interpolated up to the school district spatial level. This process will be described in detail in the *Spatial interpolation* section of this chapter. It should be noted that the ACS reports income in a discrete fashion. It provides 10 bins in across which households are distributed. Using the proportion of households found in each bin, a distribution is created from which we draw the 25th, 50th and 75th quantiles that are used in parameter estimation.

3.6.4. Public good data

The second dataset consist of spatial and site characteristic information on aquaculture produced and leases issued between 1996 and 2017. This data was provided by the Maine Department of Marine Resources (DMR). The GIS shapefile was provided by the Maine office of GIS. Data on leaseholder characteristics, lease type, lease approval and termination, acreage, species farmed, DMR notes, body of water occupied, and the corresponding GIS polygon of the lease are all included. Leases that expire before 2011 are dropped from the dataset.

These data are supplemented with information from a variety of different sources. The ACS provided Census tract-level information on high school graduation rates and population, while information on location of hospitals and libraries is gathered from the Maine Office of GIS. Each is coded as a point file in ArcGIS. Additional data on per pupil expenditures and school choice is collected from the Maine Department of Education (Maine Department of Education n.d.). School choice, also known as the Town Tuitioning Program is a curious process in Maine where certain municipalities are able to send their children to any school district they choose because that municipality does not have a school of its own. Lastly, we collect data from the Maine DMR regarding closures of shellfish harvesting areas. The National Shellfish Sanitation Program (NSSP) is tasked with classifying shellfish growing areas into four distinct categories: prohibited, restricted, conditionally restricted, conditionally approved, and approved. A prohibited classification bans any harvesting of aquaculture for any purpose; a restricted classification bars the sale of shellfish directly to market for consumption and requires depuration; a conditionally restricted classification has similar implications to the restricted classification but can be loosened under certain management plans; a conditionally approved indicates that the growing area meets the necessary benchmarks for shellfish distribution except under certain management plans; and an approved classification indicates that shellfish harvests for direct market sale is allowed. Each closure is given its own polygon in a GIS shape file. Growing areas are able to change for each NSSP determination, and there is no set time for how long a classification can persist (FDA, 2017). We use the subset of this data containing the prohibited and the restricted classifications. These designate long-term shoreline closures and act as a proxy for water quality. Collectively, this data is meant to capture the amenities that are important coastal homeowners in their household location decision.

3.6.5. Spatial interpolation

Much of the data used in estimation is gathered at the Census tract level from the ACS. To translate this data into meaningful information at the school district level, it must be interpolated by using spatial weights. Spatial weights are taken from the Missouri Census Data Center, which constructs the weights by simultaneously considering the land area, the population density, and the density of housing units in both spatial units. Continuous data uses weights that represent the proportion of the school district that contains the Census tract. For each school district, the weights should sum to one. A different interpolation technique is required for school district level discrete data like libraries and hospitals. In these cases, the weights should reflect the proportion of the Census tract that makes up the school district. To illustrate this, imagine a school district that is entirely comprised of two Census tracts where 75% of the district's population is in one Census tract and 25% lives in the other. The tract with 75% of the population has 40% seasonal homes and two libraries, the other has 20% seasonal homes and one library. To calculate the school district's *continuous* percentage of seasonal homes, we use the population shares of the Census tracts that make up the school districts as weights, such that

$$(Popshare_{Tract1} * \%Seasonal) + (Popshare_{Tract2} * \%Seasonal) = (.75 * .4) + (.25 * .2) = .35 \text{ or } 35\% \text{ Seasonal homes at the school district level}$$

Now, to interpolate the *discrete* number of libraries from the census tract to the school district level, we use the proportion of the Census tract that falls within the school district ($Popshare_{SD}$), such that

$$(Popshare_{SD1} * \#ofLibraries) + (Popshare_{SD2} * \#ofLibaries) = (1.00 * 2) + (1.00 * 1) = 3 \text{ Libraries at the school district level}$$

The GIS intersect function is used to map each point onto its respective school district for discrete data. This same process is used to determine the school district in which each home sale falls.

A different process still is used to assign aquaculture production sites and NSSP closure areas to their appropriate school districts. Using the buffer function, we create a one-mile buffer around a polyline that follows Maine's average highwater mark. This new shape is then intersected with a municipalities polygon file that extends well beyond the one-mile bound that is set. Using the calculate geometry features within ArcMap, two new columns are added: a column that represents the proportion of municipal water space within the buffer that is occupied by shellfish closure areas, and a column that measures the proportion of water space within the buffer that is occupied by an aquaculture lease.

3.6.6. The public good

As discussed previously, the term "public good" in the context of equilibrium sorting literature can be thought of as a community-specific or locally available good or service over which households hold preferences. These goods are nonmarket in their nature. The construction of the public good must be done with great care. The choice of goods to include in the public good are of critical importance to producing accurate estimates because the household locational choice is assumed to be dependent entirely on those goods and community price. For our model, we look to the literature for choices that are conventionally included.

3.6.6.1 School quality measures

There are several amenities within the public good that are ubiquitous throughout the literature. Things like school quality (Bayer et al., 2004a; Bayer et al., 2004b), air quality (Sieg et al. 2004; Tra 2010) and access to urban amenities (Kuminoff et al., 2013; Epple & Ferreyra 2008) are popular choices. In this thesis, school quality is captured by the total expenditures a school district spends on each of its students. While school quality is often measured by reported standardized test scores, the availability of the needed data in Maine is limited. Instead, we assume that school districts that spend more money on each student are more likely to produce higher gains on education.

School choice is also considered, not necessarily as an element of school quality, but instead as an independent amenity. School choice provides flexibility to the parents who own households in communities where it is offered by allowing them to send their child to any school they choose. The voucher program that makes this possible ensures no additional cost to the parent, making it an exceptionally appealing program. School choice enters the public good as a dummy variable indicating that a school district either provides or does not provide a choice. School districts that provide school choice tend to map directly onto single municipalities such that they are one in the same. This allows for the binary choice.

Besides income, other measures of general community quality are included in the public good. High school graduation rates are used as a way to measure affluence of any given community. While high school graduation rates are not common in the sorting literature, we include them here as a means of subsidizing our measure school quality, per pupil expenditures. Together they create a compelling proxy for school quality in lieu of standardized test scores.

3.6.6.2. Access to urban amenities

Measures of access to urban amenities are included throughout much of the sorting literature. This research is placed at a curious crossroads in that it is one of only a few studies to employ a PC model in a strictly non-urban setting. As such, a certain amount of creativity is necessary when constructing the urban variable. Popular choices for urban amenities include the presence of libraries, hospitals, shopping malls, and public parks. For the latter two, there is an absence of variation across each of the regions of study. We calculate two urban variables that become a part of the public good index. The first is a simple measure of the number of libraries within a school district. This is a rudimentary tool and has several shortcomings. First and foremost, a simple count of libraries does not account for population distributions across school districts. For example, it is possible to have two school districts where the first has more libraries, but the bulk of the population is farther from those libraries because of the way households are distributed across the school district. The second school district could have fewer libraries, but households are more consolidated around them, and thus the access to these amenities may be greater in the district with a smaller count.

A second urban variable is introduced to capture the sometimes-odd spatial distribution of households around urban amenities in coastal Maine. We calculate the median distance of every household in a school district to a hospital. A hospital can be Tier 1, Tier 2, or Tier 3 with the majority of hospitals in Maine being small, or Tier 3 hospitals. The median distance is calculated, instead of mean distance, to avoid the strong effects of outliers.

3.6.6.3. Coastal amenities

One of the more difficult aspects of this research is determining how marine amenities influence the choices made by terrestrial households. Maine’s coastal communities are comprised of complex networks of resources and resource users. The interactions and relationships between these different resources can be challenging to tease apart, but understanding the dynamics is imperative to creating a clear picture of the effects of each resource component. Take for example the relationship between aquaculture and commercial fishing. Commercial fishing is a big industry in Maine, with production value estimated at approximately $637 million in 2018 (DMR, 2019). The production of aquaculture relies heavily on the infrastructure provided by the commercial fishing sector, such that it is difficult to tease out the impact that changes in aquaculture could have on coastal housing markets without simultaneously considering commercial fishing. We include three variables in the public good that account for these marine resources: a measure of working waterfront, a measure of water quality, and a measure of aquaculture production.

To assess how each community's coastal space is being used, we create a measure by determining the percentage of seasonal homes in each community. The intuition is that communities with high levels of seasonal homes have tourist-driven economies. In turn, communities with more tourist driven economies are likely to have coastal space distributed differently than those communities who do not depend on tourism. Maine's coastline can have drastically different degrees of tourist activity even in spatially adjacent communities.

Water quality is calculated directly from the proportion of NSSP classified shellfish harvest closures. While it is tempting to utilize a more obvious measure of water quality like turbidity, chlorophyll levels, or salinity, these measures are not salient to households. The NSSP classification process requires physical closures of coastline until the water quality is deemed safe through a comprehensive review process (FDA, 2017). Coastline closures are readily apparent to homebuyers. Only long-term closures are counted because short-term closures that appear in conditionally approved and conditionally restricted classifications will often not be observed by the households. There are other advantages to using NSSP classifications. Because

NSSP closures explicitly prohibit the harvesting of shellfish, the presence of long-term closures is endogenous to aquaculture site selection, as the two are mutually exclusive.

3.6.6.4. Aquaculture

The final component of the public good may be the hardest to define and accurately capture. Aquaculture siting locations in Maine take up relatively little marine space but are subject to intense regulatory and public scrutiny. The idiosyncratic nature of the leasing process coupled with the heterogenous nature of preferences among Maine's coastal residents has led to a complicated and spatially interesting landscape with regards to both the clustering of aquaculture across the state and the perceptions of coastal homeowners who inhabit those areas. Furthermore, the spatial-temporal volatility of aquaculture makes it exceedingly difficult to accurately capture marginal, let alone nonmarginal effects. In this section, we detail our method of constructing a variable that adequately captures the influence of aquaculture on coastal homeowners.

Recall that the goal is to assess the nonmarginal impacts of aquaculture change on a community level. As such, the spatial relationships between all households in a given community and the aquaculture that is believed to influence homeowners buying decisions must be simultaneously considered. We explored two alternative specifications for aquaculture. For the first specification, several important assumptions about aquaculture and its relationship to a community need to be made. First, we acknowledged that it is possible that there is a size-distance ratio at which aquaculture will cease to influence a community. For this specification of aquaculture, the decay effect is modeled as a spatial weight which takes a tri-cube form. This implicitly assumes that larger amounts of aquaculture production close to a community has a strong effect that tapers quickly and then levels off as distance becomes large or production area becomes small, and can be seen as:

$$w(d_{jk}) = (1 - (d_{jk}/q_i)^3)^3 * I(d_{jk} < q_i)$$

where j is the relevant community, k is the aquaculture associated with that community, q_i is a distance unit, and I is an indicator function. q_i is set to one mile, following Evans et al. (2017). When $d_{jk} < q_i, I(\cdot) = 1$ and when $d_{jk} > q_i, I(\cdot) = 0$.

Second, we assume that the leasing process described in the background section is strongly related to the preferences held by households at a municipal level. That is, because leasing decisions are ultimately made on a town-by-town basis, households only hold preferences over aquaculture leases that fall within the bounds of their municipal waters.

Our third assumption relates directly to how the distance from a community to aquaculture is measured. Municipal population centers are generated by identifying the household that minimizes overall distance to each of the home sale locations in our data. While it may seem intuitive to measure the distance from a point on a community's coastline or a community centroid, it does not accurately capture how the households are distributed across a community, and by extension, how each of those households will be affected by changes in aquaculture. By identifying the median of housing sale points in our data for each municipality, we are effectively creating proxy for a downtown area where the distance from point to each aquaculture siting location within municipal waters is calculated.

Fourth, we assume that household preferences over aquaculture are not dictated simply by the spatially weighted number of acres occupied in each municipality, but rather by a ratio of acres used for aquaculture production and the total number of acres available in municipal waters. Ultimately, aquaculture enters into the model as a constrained distance-weighted ratio of aquaculture acreage to available space. This can be written as:

$$AQ_j = \sum_{k \in A_j} w(d_{jk}) * a_{jk}/T_j$$

where A_j is the set of all aquaculture leases, a_{jk} is the acreage used to produce aquaculture in community j, and T_j is the total amount of available water space.

Finally, we assume that the differences in the leasing process between LPAs, standard leases, and experimental leases yield differences in household preference. That is, because households are able to participate in the process of a grower acquiring a standard lease, those households value the presence of that lease differently than they would an LPA, where they have no input in the leasing process. We estimate two models: one where aquaculture lease types are homogenous in their impact on coastal homeowners, and a second where households can hold different preferences over different types of aquaculture leases. Broadly, this implies that households not only value how much relative aquaculture is in their community and how far away from them it is, but that they also value having input into the leasing process.

The second specification of aquaculture is much simpler but may capture the most important aspects from the perspective the home buyer. Instead of constructing a list of assumptions to which the index must adhere, the relationship between the community's preferences and the amount of aquaculture production space hinges solely on the total available coastline to that community, and the total amount of area dedicated to aquaculture production within one mile of the coastline. Ultimately, it is this specification that is used. By including a variable that measures the total coastline available, we directly control for the coastal space available in each community. As such, measuring aquaculture directly by acreage will allow for easy marginal interpretation and also capture the effects of production proportionally to the coastline available to each community, much like a single aquaculture density variable would.

Maine is a challenging place to employ a PC model because of its rural nature and its curious treatment of school districts. This is why amenities that are so often included are omitted in this chapter. For example, air quality appears frequently throughout the sorting literature, but in Maine it is almost completely homogenous. A lack of variation stymies the use of other variables that otherwise would've been included. Demographic variables like race also do not vary in Maine, as it is one of the oldest and whitest state in the U.S. (U.S. Census Bureau, 2018). The amenities that are a part of the pubic good we consider to be integral to correctly characterizing the sorting process. There is always the temptation to include more sources of variation across communities, but equilibrium sorting models rely on parsimony to produce accurate predictions.

3.6.4. Counterfactual data

PC models require further validation if they are to be more widely accepted as a tool that can be used for providing policy recommendations (Evans, 2011; Kuminoff et al., 2010). In practice however, it can be challenging to validate model predictions against observed outcomes. In this chapter, we use data collected between 2012 and 2014 to construct our baseline scenario and generate parameter estimates. Data was collected across 2015 and 2016 to generate the observed counterfactual. For most model inputs, data was collected from the same source and interpolated in the same way. The main exception was that of housing expenditures. Because housing transactions data is only available between 2012 and 2014, we collect binned housing expenditures data from the ACS, which is made to be continuous by following the same process used to create income quantiles. Once counterfactual data is collected, it is possible to conduct validation exercises. However, none are conducted in this thesis.

3.7. Results and Discussion

3.7.1. Estimation results

While all models found $\rho < 0$, indicating that the single-crossing condition was satisfied, the models for each of the three regions produced results that were not in line with expectations. As such, two sets of results are reported. Within each set, a general and partial WTP is reported for each region. The first set of results, coming from what will be referred to as the unconstrained models, estimate *all* of the parameters used to produce WTP estimates (See Table B.6.). Willingness-to-pay estimated by the unconstrained models is negative for Casco Bay, Damariscotta River region, and Penobscot Bay in both the partial and general equilibrium setting. However, the general equilibrium results suggest that the mean household WTP approaches infinity. The partial equilibrium WTP are finite but again, they do not match our expectations by an order of magnitude. At first blush, the model appears to be unbounded by income. However, WTP should only be bounded by income if it is positive. If the WTP is negative, it can be thought of as a willingness-to-accept (WTA), which is intuitively unbounded.

The seconds set of WTP estimates is constrained in several of its parameters (See Table B.7). We calibrate the parameters for constant price (ω) and income elasticities (γ), as well as the CES substitution (ρ) parameter. Parameter estimates used to calibrate the constrained models were borrowed from Sieg et al. (2004) and Evans (2011) and can be found in Table B.4. Complete tables of parameter estimates from both the unconstrained and constrained models can be found in Tables B.6. and B.7. respectively. Since the constrained models use parameters that are not generated directly from the data, the resulting WTP estimates should not be regarded truly as estimates. Instead, constrained estimates operate as part of a thought experiment, where sensitive parameters are calibrated in an attempt to match the magnitude of results found in previous work. Willingness-to-pay results from the constrained and unconstrained models can be found in Table B.8.

The calibration exercise demonstrates that the model is highly sensitive to each of the parameters that capture an aspect of substitution in the model. With constraints imposed on these elasticities, the model produces results with a magnitude that are mostly consistent with expectations. Willingness-to-pay is an order of magnitude higher than those found in Evans et al.

(2017), but this is not entirely surprising. Due to the nature of the nonmarginal increases of aquaculture between the baseline and counterfactual data, larger WTP estimates make sense. Additionally, the substantive differences in WTP between the partial and general equilibrium settings are intuitive; the partial equilibrium WTP does not allow households to respond to changes in amenities by moving communities where the general equilibrium framework does. For each region, the general equilibrium WTP is higher than that of the partial equilibrium suggesting that giving households a locational choice is important when the impacts of large-scale environmental changes are being estimated.

The unconstrained model also produces relative changes in community price which can be used to understand how changes in aquaculture and correlated amenities might be perceived by coastal resource users. By examining community level changes in rank ordering given a change in the landscape, it is possible to determine how coastal communities may react to a more general redistribution of their coastal resources. Communities who may benefit the most from a redistribution of coastal space see improvements in their relative community price, while those communities who see their relative price fall may prefer to see the coastal economy remain the same. Note that changes in community ranking cannot be induced through endogenous variables due to the structure of the ranking instruments (Kuminoff, 2013a). The effects of changing aquaculture are most salient when viewed through a relative price change. Figures B.4. through B.6. illustrate how changes to aquaculture in the calibrated model illicit changes in community price (and price ranking). Additionally, tables detailing the price changes can be found in Table B.9.

3.7.2. Sensitivity tests

We assert that the unconstrained model's results may be inconsistent with expectations because of a misspecification of the public good. Note that the structure of the model leaves it especially vulnerable to omitted variable bias (the variation of endogenous omitted variables is captured only by other variables within the public good, not an error term). To isolate potential problematic variable(s) within the model, several model specifications and counterfactual scenarios are estimated. First, we estimate WTP in the unconstrained model with the observed counterfactual data, which yields a mean general equilibrium WTP of -$\$\infty$ for two of the regions. In response, a second model estimates WTP with only a five percent increase in the provision of aquaculture, while holding all other variables (including community income and housing expenditure quantiles) constant. This produces the same result, indicating the variable intending to capture aquaculture may be capturing much more. The way aquaculture enters the model can have an impact on results, so both specifications found in the *Public Good* section of this thesis are modeled. We find improvements in magnitude from -$\$\infty$ to -$171,860 in the Damariscotta River region with the second specification.

3.8. Future work

This chapter highlights the sensitivity of a group of models that is seeking further validation in the economic literature. Our results were not in line with those of previous studies, which could be due to a misspecification of the public good or a product of imposing high levels of structure on a relatively small sample. We have some suggestions for moving forward that will help transform this model into a useful tool for policy analysis. Of all the decisions the econometrician makes when constructing a pure-characteristics equilibrium sorting model, two stand out.

The first: deciding which amenities should be included in the public good. We largely followed the literature in constructing the public good for the model presented in this thesis, but the literature has not yet examined an area as rural as coastal Maine. This led to unique challenges. Variables representing the urban-rural spectrum have been used throughout the sorting model literature and typically use amenities like population density and access to urban amenities. In generally urban environments, the researcher can often find colorful variation in these measures which are helpful in explaining relative differences in the level of urbanity. In overwhelmingly rural environments like the one being presented here, standard measures of urban and rural do not provide helpful variation. What is needed is a different way to measure the urban-rural divide. Moving forward, this public good should include relative measures of urban and rural that better capture the availability of Maine's "urban" amenities.

A larger potential issue with the public good could be the omission of amenities endogenous to aquaculture. While data is hard to come by, it is imperative that the model control for other uses of coastal space that could be correlated with aquaculture production. First and foremost, the public good must include variables that account for commercial fishing which is a hugely important component of Maine's coastal economy. Additionally, much of the infrastructure that Maine's aquaculture industry depends on is primarily used by commercial fishers. In its current state, the aquaculture variable is likely capturing nearly all of the effects of correlated coastal resources, which in turn is causing the model estimates to explode. The inclusion of variables that capture commercial fishing output may well solve many of the model's problems.

The second decision that can heavily influence results is the choice of community. Again, in this thesis we follow the literature by using school districts as our unit of analysis. This is a popular choice because school quality is widely considered a major factor in determining household locational choices. However, there are three possible issues with this choice in this thesis. First, school districts in Maine are poorly defined. District boundaries are constantly being drawn and then redrawn as populations and budgets change. There is also a litany of impressively small school districts that inhabit the islands of coastal Maine and the more rural areas of the coast. Second, nearly all of the data used in this thesis are gathered at the census tract or municipal level. Choosing a different unit of analysis may reduce measurement error. Third, the amenity of interest (aquaculture) is regulated at a municipal level. The leasing process encourages aquaculture production areas to vary spatially across municipalities, not school districts. You may have a school district composed of two municipalities where one allows aquaculture and the other does not. There would be two opposing "community" preferences, but they would be aggregated into a single entity, diluting the true preferences of both groups.

Pure-characteristics equilibrium sorting models are fickle in nature and require deep thought and care in their preparation. The work presented in this thesis can be built upon to provide even deeper insights into aquaculture siting decisions. Modifications to the public good that fall outside of the current literature may help produce estimates that are more compatible with previous work. In particular, careful consideration should be given to possible endogenous regressors to aquaculture. A change in the spatial unit of analysis may also be prudent. In a break with tradition, it may be necessary to aggregate and analyze data at the municipal level to account for the siting process. The resulting model could have powerful policy implications by informing policymakers about how to socially optimize aquaculture siting decisions.

3.9. Conclusions

This thesis chapter estimates a general equilibrium WTP for nonmarginal changes in aquaculture production across three regions of coastal Maine. A pure-characteristics equilibrium sorting model is identified as the correct tool for analysis and is used to model household preferences for aquaculture and a slate of other goods. However, the willingness-to-pay estimates produced were of a different order of magnitude than expected. By constraining certain parameters as part of a thought experiment, the model was able to produce results that were of the expected magnitude, suggesting that the model's sorting process may be particularly sensitive to the values assumed by those parameters. Still, we learn a great deal about the preferences of households within each community by examining relative changes in community price.

The presence of omitted variables in the public good can have massive implications for the weights the model places on the variables that are included. In this case, the omission of measures of critical coastal resources like commercial fishing and other endogenous covariates may be hyperinflating the impact aquaculture has on the housing decision. Additionally, the sensitivity of the model to the constraints we place on parameters can have huge effects on results. For example, it is possible to constrain price and income elasticities, and the demand intercept such that the model produces results (more) in line with expectations, however this undermines one of the main advantages of the model in that the parameters are estimated, not calibrated. More work needs to be done to extract the effects of aquaculture from other coastal resources that are more impactful on housing markets.

Still, this chapter produces some compelling qualitative results. The model uncovered relative changes in community price that can still be useful to policymakers. By examining relative changes in the price on a community by community basis, it is still possible to interpret how sensitive a community might be to changes in its coastal system. The implications of this cannot be understated. Expanding aquaculture production in the State of Maine is best achieved if the heterogeneity in preferences of coastal resource users is used to the advantage of policymakers and stakeholders. Coordinating siting locations in communities where aquaculture improves the quality of a community is mutually beneficial to the homeowners and the growers.

CHAPTER 4

CONCLUSIONS

This thesis explores two serious impediments to sustainably growing Maine's aquaculture sector. In doing so, it also contributes to two bodies of literature: one focused on off-farm labor participation and one focused on valuing environmental resources within an equilibrium sorting framework.

Chapter 2 looked to explain how the propensity of aquaculture growers to participate in off-farm labor varies along a number of dimensions. We tested a series of discrete choice and count models to identify important factors driving both the decision to participate in off-farm labor, and if so, how much to participate. This study found that off-farm labor in New England's aquaculture sector is driven by many of the same factors that are known to influence off-farm labor decisions within an agricultural context. The study also finds that variables that measure marine climate and the amount of information growers receive are important in determining how much off-farm labor a grower will supply. We develop a new analytical approach to estimate parameters by introducing new and relevant variables to a traditional off-farm labor model and by utilizing count models, which are rare in the literature, to estimate the effects of the covariates.

Chapter 3 sought to uncover the effects of changes in aquaculture production area in three regions of coastal Maine. Building off the work of Evans et al. (2017), we constructed a model aimed at understanding how nonmarginal increases might influence welfare on a community by community basis. Using a pure-characteristics equilibrium sorting model, we estimated willingness-to-pay in both partial and general equilibrium settings. Results were not of the expected magnitude, which led to intensive sensitivity checks of the model. We determined that aquaculture is likely endogenous to other coastal amenities that were not specified. Still, a deeper understand of aquaculture's role in the coastal economy is gained. Communities have drastically different responses to changes in their coastal economic system, suggesting a wide range of preferences may be held over how coastal space is used.

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APPENDIX A: TABLES AND FIGURES FROM CHAPTER 2

Table A.1. Summary statistics for variables used in off-farm labor analysis.: Data was collected in a 2016 survey of all oyster growers in New England. One hundred and forty-five usable responses were returned. For each response, three years of information was included. We collect information on demographic and business characteristics, climate, and local economic conditions. Each observation (N) is one year of data from a grower.

Description	Variable	N	Mean	SD
Non-Binary Variables				
Average weekly hours spent doing off-farm labor	*OFL*	423	15.28	19.54
Number of years farm has been in operation	*YearsActive*	420	10.00	9.23
Annual oyster harvest (thousands of pieces)	*TOH*	300	469.8	1103.3
Age of respondent	*Age*	422	56.33	13.97
Square of the respondents age	*Age_sq*	422	3367.60	1510.08
Number of children who are of school age (below 18)	*SAC*	417	0.46	0.87
Number of years of education the grower has received, starting at first grade	*YOS*	420	15.19	2.44
Number of people per square mile	*Popdensity*	418	45.82	113.04
Inches of rain a farm receives annually	*Precip*	420	47.92	5.38
Average water temperature of farm measured in Celsius	*Water_Temp*	423	5.16	1.31
Percentage of adults in a zipcode population that is unemployed	*Employment*	393	8.61	8.46
Distance in meters to nearest zipcode population of 10,000 or more	*Urban*	417	7.55	7.65
Number of times listed by another grower in the same state (Information sharing)	*SNL*	423	2.43	2.75
Dummy Variables				
Grower operates in Maine	*Maine*	423	0.23	0.42
Grower raises other species	*OtherSpecies*	420	0.19	0.39
Grower is a man	*Gender*	423	0.89	0.32
Grower is married or engaged	*Married*	423	0.77	0.42

Table A.2. Probit and logit results.: Probit and logit models are estimated to determine significant factors in a grower's choice to participate or not participate in off-farm labor. Estimates can be interpreted for sign and direction, but cannot be understood as marginal effects. Variable descriptions can be found in Table A.1.

	Probit Model		Logit Model	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.
Maine Dummy	-0.6175	0.4830	-0.9552	0.8369
Years Active	0.0334**	0.0154	0.0584**	0.0263
Other Species Dummy	0.8111**	0.3186	1.4955**	0.5936
Total Oysters Hauled (thousands)	-0.0003*	0.0002	-0.0006*	0.0003
Age	0.0772	0.0577	0.1169	0.0991
Age Sq. Interaction	-0.0010*	0.0005	-0.0016*	0.0009
Gender	0.8188**	0.3238	1.4130**	0.6094
Married/Engaged Dummy	1.0700***	0.2614	1.8008***	0.4422
School Aged Children	0.1915	0.1337	0.3400	0.2323
Years of Schooling	0.0934*	0.0550	0.1581*	0.0953
Population Density (thousands/sq_mile)	11.1537***	4.4197	18.4381**	7.6905
Precipitation	0.0089	0.0274	0.01600	0.0478
Water Temperature (C)	-0.5677***	0.2149	-0.9518***	0.3662
ZIP Unemployment	-0.0059	0.0112	-0.0099	0.0183
Urban	0.0077	0.0146	0.0084	0.0254
Information Sharing	0.3057***	0.0633	0.5181***	0.1087
2013	1.3831**	0.6753	2.3246**	1.1447
2014	0.6777*	0.3964	1.1677*	0.6723
Constant	-3.0914	2.0910	-4.8747	3.5114

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively

Table A.3. Estimates from count models and zero-inflated count models.: Parameter estimates are recovered from the Poisson model, the negative binomial model, the ZIP model, and the ZINB model. The positive finds section of the ZIP and ZINB models can be compared to those of the Poisson and negative binomial. The logit selection section of the ZIP and ZINB findings are the results from a model estimating the probability a grower will choose to participate in off-farm labor. These results can be interpreted as a percent change in the conditional mean of off-farm labor hours worked. AIC and BIC statistics are also reported, and are helpful in determining the best model. Variable descriptions can be found in Table A.1.

Parameter	Poisson Model		Negative Binomial Model		ZIP Model		ZINB Model	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
					Positive Finds			
Maine Dummy	-0.1511**	0.068208	-0.6047	0.56227	-0.0354	0.0741	-0.1751	0.2231
Years Active	-0.0038*	0.001972	-0.0029	0.01847	-0.0187***	0.0021	-0.0237***	0.0071
Other Species Dummy	0.4762***	0.034041	0.7507**	0.32794	0.09239***	0.0345	0.0876	0.1171
Total Oysters Hauled (thousands)	-4.52E-04***	3.63E-08	-7.10E-04***	2.51E-07	-2.95E-04***	4.37E-05	-3.18E-04**	1.24E-04
Age	0.1327***	0.010413	0.0867	0.0639	0.0949***	0.0094	0.0937***	0.0275
Age Sq. Interaction	-0.0014***	0.0001	-0.0011**		-0.0009***	8.95E-05	-0.0009***	0.0003
Gender	1.0443***	0.071397	1.3564***	0.0006	0.7918***	0.0715	0.9555***	0.2157
Married/Engaged Dummy	0.2945***	0.041298	0.6817**	0.4110	-0.0984**	0.0428	-0.0994	0.1375
School Aged Children	0.0139	0.017456	-0.06305	0.3055	0.0032	0.0169	-0.0630	0.0584
Years of Schooling	0.1252***	0.007336	0.1760***	0.1425	0.0980***	0.0078	0.1130***	0.0259
Population Density (thousands/sq_mile)	0.0013***	0.00017	0.0016	0.0643	0.0003*	0.0002	0.0005	0.0005
Precipitation	-0.0115***	0.004035	0.0056	0.0014	-0.0129***	0.0042	-0.0140	0.0137
Water Temperature (C)	-0.2217***	0.023923	-0.5746***	0.0314	-0.1790***	0.0246	-0.2416***	0.0778
ZIP Unemployment	-0.0009	0.001927	0.0077	0.2135	-0.0053***	0.0019	-0.0020	0.0060
Urban	0.0060***	0.002193	-0.0224	0.0136	0.0027	0.0023	-0.0041	0.0072
Information Sharing	0.0275***	0.007119	0.1435**	0.0167	-0.0585***	0.0074	-0.0554**	0.0236
2013	0.4016***	0.07735	1.4089**	0.0652	0.3906***	0.0809	0.5109*	0.2617
2014	0.2054***	0.051105	0.7587*	0.7094	0.2132***	0.0519	0.2773**	0.1658
Constant	-1.6275***	0.369447	-0.8960	0.4242	0.5809*	0.3415	0.6968	0.9872
					Logit Selection			
Maine Dummy					0.9539	0.8370	0.935903	0.8425

Table A.3. *Continued*

Years Active	-0.0584**	0.0263	-0.06286	0.0282
Other Species Dummy (thousands)	-1.4959**	0.5937	-1.64653	0.6953
Total Oysters Hauled	5.66E-04*	3.07E-04	5.56E-04	3.10E-04
Age	-0.1167	0.0991	-0.11196	0.0999
Age Sq. Interaction	0.0016*	0.0009	0.0016	0.0009
Gender	-1.4119***	0.6096	-1.2157	0.7586
Married/Engaged Dummy	-1.8014	0.4422	-1.8356	0.4533
School Aged Children	-0.3400*	0.2323	-0.3691	0.2476
Years of Schooling	-0.1582**	0.0953	-0.1535	0.0965
Population Density	-0.0184	0.0077	-0.0192	0.0080
Precipitation	-0.0160***	0.0478	-0.0168	0.0481
Water Temperature (C)	0.9519	0.3662	0.9746	0.3749
ZIP Unemployment	0.0099	0.0183	0.0094	0.0184
Urban	-0.0084	0.0254	-0.0099	0.0260
Information Sharing	-0.5180	0.1087	-0.5160	0.1093
2013	-2.3246	1.1446	-2.3881	1.1635
2014	-1.1677	0.6723	-1.2014	0.6838
Constant	4.8718	3.5112	4.5488	3.5826

Summary statistics

N	272	272	272	272
AIC	5588.242	1899.421	2348.751	1662.008
BIC	5656.753	1971.537	2485.772	1802.635

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively

Table A.4. ZINB marginal effects.: Marginal effects from the zero-inflated negative binomial model are estimated. Coefficients can be interpreted as the expected change in the number of off-farm labor hours resulting from a one unit change in non-binary variables. Binary variables can be interpreted as the expected change in off-farm labor hours worked when compared to the base. Variable descriptions can be found in Table A.1.

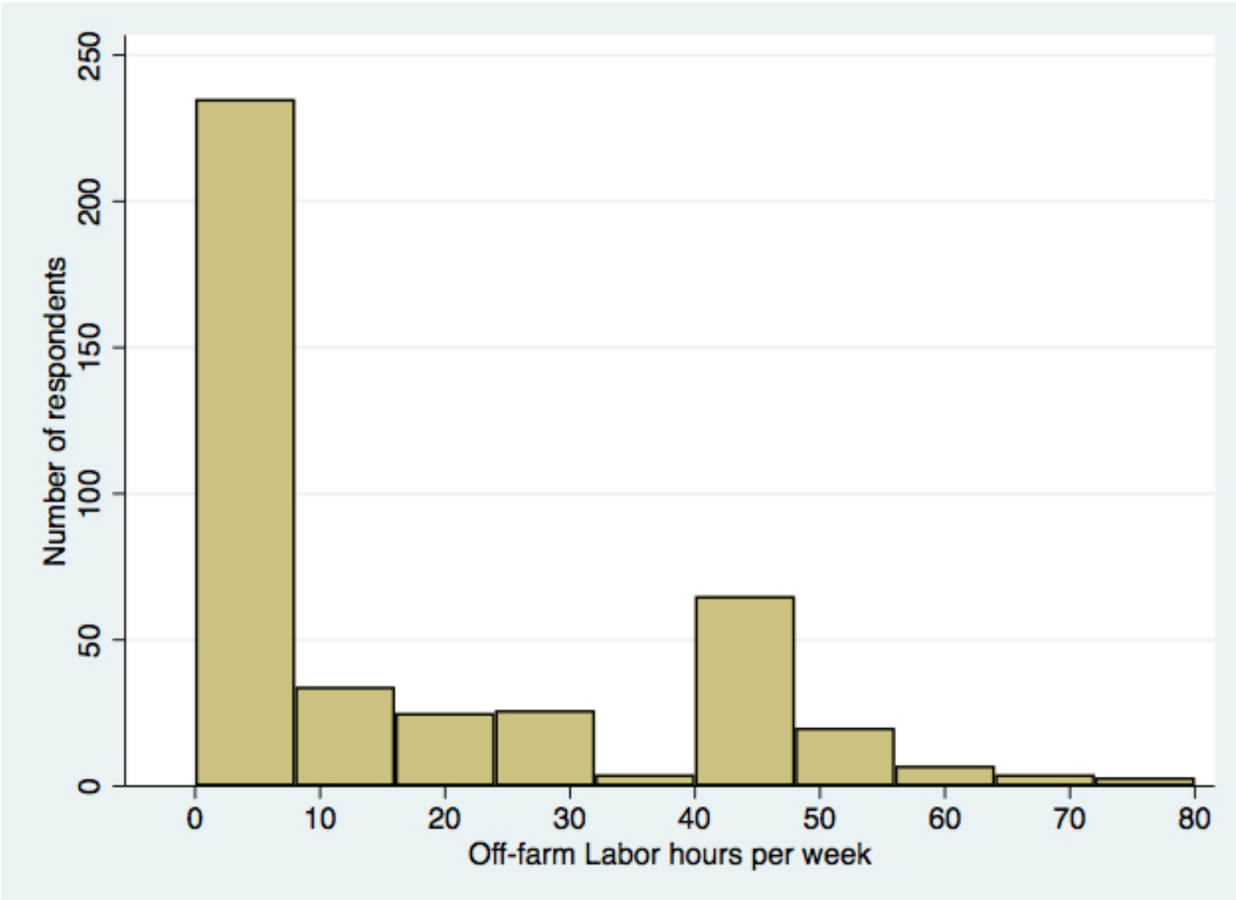
Variable	Marginal Effects	Standard Error
Maine Dummy	-4.9345	6.7170
Years Active	-0.6947***	0.2148
Other Species Dummy	2.9896	3.5075
Total Oysters Hauled (thousands)	9.64E-3**	3.83E-3
Age	0.0231	0.1197
Gender	27.5759***	6.1482
Married/Engaged Dummy	-2.9613	4.1602
School Aged Children	-1.7331	1.7226
Years of Schooling	3.3825***	0.8160
Population Density (thousands/sq_mile)	0.0129	0.0156
Precipitation	-0.4332	0.4128
Water Temperature (C)	-7.3150***	2.4159
ZIP Unemployment	-0.0646	0.1820
Urban	-0.1103	0.2120
Information Sources	-1.7125**	0.7222
2013	15.4488*	7.9890
2014	8.4042*	5.0496

Table A.5. Likelihood ratio tests and Vuong tests results.: The Vuong tests compare the zero-inflated models to their respective standard models. Results indicate that the zero inflated models are the appropriate choice. Likelihood ratio tests are used to test if alpha is significantly different from zero, which justifies the use of a negative binomial distribution instead of a Poisson distribution. The likelihood ratio test suggest that the alpha is different from zero, and thus the data not equidispersed.

Model	**Preferred Model**	**Likelihood Ratio Test**
Poisson vs Negative Binomial	Negative Binomial	chibar^2 = 3698.75***
Zero Inflated Negative Binomial vs. Zero-Inflated Poisson	Zero-Inflated Negative Binomial	chibar^2 = 686.40***
		Vuong Test
Poisson vs Zero- Inflated Poisson	Zero-Inflated Poisson	z = 11.66***
Negative Binomial vs. Zero-Inflated Negative Binomial	Zero-Inflated Negative Binomial	z = 10.86***

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively

Figure A.1. Weekly off-farm labor participation by respondent.: Provision of off-farm labor (hours) was collected in a 2016 survey of New England Oyster Growers. Three distinct classes emerge: one at zero hours, one between zero and 40 hours, and one at 40 or more hours.



APPENDIX B: TABLES AND FIGURES FROM CHAPTER 3

Table B.1. Differences between the three types of sorting models (modified from Kuminoff et al. (2013)).: Different sorting models are distinguished by their treatment of the household choice, the treatment of substitute goods, the presence of a budget constraint, and the instruments used to deal with endogenous sorting among other things.

	Random Utility (RU)	Calibrated Sorting (CS)	Pure-Characteristics (PC)
Choice	House | Job	House, school, vote	House
Budget Constraint	Yes	No	Yes
Differentiation Type	Horizontal	Horizontal	Vertical
Model Instruments	Attributes of substitutes and amenity discontinuity	Production function	Income Rank

Table B.2. Household summary statistics by region.: Data from housing transactions from January 2012 through December 2014 was used to determine relative community price. Distance to Water measures the distance from each household to the closest planar point of coastal Maine.

	Casco Bay (N = 6,112)		Damariscotta River (N = 2,316)		Penobscot Bay (N = 1,678)	
Home Characteristics	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Sales Price ($1,000s)	318.53	280.11	216.28	229.36	272.99	328.93
Lot Size (acres)	1.22	5.02	4.07	45.93	3.21	7.27
Living Area (square feet)	2030.85	981.50	1775.04	866.20	1898.20	1068.46
Bathrooms	1.99	0.87	1.77	0.803	1.92	0.95
Bedrooms	3.25	0.84	2.98	0.85	3.04	1.00
Age (years)	59.06	45.72	70.56	82.62	73.18	90.57
Distance to Water (miles)	1.03	1.39	1.02	1.38	1.03	1.41

Table B.3.: Fixed-effects hedonic regression. Hedonic analyses are used to find the relative price of each community by controlling for each household's structural, neighborhood, and environmental characteristics. The base estimate for each region is zero. The school district with the smallest coefficient estimate is normalized to one. Annual fixed-effects are included to capture major shifts in the real estate market between 2012 and 2014.

Control Variables	Casco Bay		Damariscotta River		Penobscot Bay	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Lot size (100 acres)	0.713***	0.093	-0.039	0.024	1.79***	.202
Square feet (1,000s)	0.266***	0.009	0.283***	0.019	.156***	0.021
Bathrooms	0.178***	0.009	0.239***	0.021	0.311***	0.024
Bedrooms	-0.047***	0.007	-0.022	0.016	-0.040**	0.019
Age (50 years)	-0.047***	0.015	-0.103***	0.011	-0.110***	0.014
Age squared	0.007***	0.003	0.002***	0.000	0.002***	0.000
Distance to water(miles)	-0.072***	0.009	-0.030	.022	-0.112***	0.027
Distance sq to water	.010***	0.002	0.004	0.004	0.015***	0.004
Casco Districts						
Long Island	Base	-				
Brunswick	-0.420***	0.091				
Cape Elizabeth	0.062	0.092				
Falmouth	-0.157	0.092				
Portland	-0.153*	0.091				
South Portland	-0.171*	0.091				
Yarmouth	-0.016	0.092				
RSU 51	-0.117	0.092				
RSU 75	-0.270***	0.091				
Chebeague	-0.028	0.119				
RSU 01	-0.606***	0.091				
RSU 05	-0.135	0.092				
West Bath	-0.337***	0.100				
Damariscotta Districts						
Augusta	Base	-				

Table B.3. *Continued*

Boothbay	0.721***	0.042
Bristol	0.728***	0.051
Edgecomb	0.557***	0.084
Georgetown	0.747***	0.077
Damariscotta	0.518***	0.072
Nobleboro	0.609***	0.080
RSU 11	-0.045	0.041
RSU 40	0.235***	0.043
South Bristol	0.877***	0.077
Southport	1.108***	0.101
RSU 02	0.195***	0.039
RSU 12	0.263***	0.042
Newcastle	0.584***	0.070
Bremen	0.637***	0.104
Penobscot Districts		
Brooklin	Base	-
Brooksville	0.330**	0.155
Castine	0.033	0.145
Deer Isle-Stonington	0.046	0.115
Islesboro	0.113	0.159
Penobscot	-0.186	0.153
RSU 28	0.111	0.106
RSU 07	0.400**	0.201
RSU 08	-0.038	0.140
Sedgewick	-0.249*	0.143
RSU 13	-0.219**	0.104
RSU 20	-0.564***	0.113
RSU 25	-0.682***	0.108
Lincolnville	-0.176	0.116

Table B.4. Descriptive statistics for school districts.: Data is collected on housing expenditures, income, and components of the public good for each region. Housing expenditures and income are reported as quartiles.

	Casco Bay (N = 13)				Damariscotta River (N = 15)				Penobscot Bay (N = 14)			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Community size (pop share)	0.077	0.027	0.022	0.126	0.056	0.022	0.014	0.109	0.063	0.012	0.051	0.083
Community price (relative)	1.451	0.201	1.000	1.687	1.558	0.334	1.000	2.187	1.629	0.317	1.000	2.165
Per pupil expenditures ($)	12503.88	961.80	11150.08	14912.81	12618.19	2208.88	8959.69	17888.92	14191.33	6724.915	6783.85	27668.85
School choice (dummy)	0.231	0.439	0.000	1.000	0.667	0.488	0.000	1.000	0.429	0.514	0.000	1.000
High school graduation rate (%)	94.86	3.15	89.27	98.59	93.02	2.52	86.18	95.83	91.05	3.76	81.33	95.96
Seasonal homes (%)	51.0	25.7	17.4	98.1	60.0	24.9	00.0	86.1	64.6	23.7	12.8	84.8
Libraries (#)	3.31	4.59	0.00	17.00	3.40	2.56	0.00	10.00	2.43	2.85	1.00	11.00
Distance to hospital (meters)	3.824	1.732	1.478	6.292	5.103	2.072	1.697	9.442	8.727	3.615	1.703	15.262
NSSP closure (%)	12.3	15.9	0.05	60.2	10.4	8.9	3.9	30.1	8.3	6.6	0.6	26.2
AQ (acres)	8.846	13.923	0.000	51.910	33.084	77.060	0.000	250.258	6.244	10.148	0.000	34.730
Coastline (miles)	83.240	112.972	6.660	394.410	64.068	47.141	1.939	141.577	88.871	87.062	7.304	284.276
Income 25 ($)	38782	15090	20000	62500	28166	2914	21049	30000	23169	4305	20000	33392
Income 50 ($)	60368	14224	34167	83217	51703	6749	41250	62500	47870	8939	36250	62500
Income 75 ($)	111831	39032	62500	175000	81766	7740	62802	87500	78678	14528	62500	112500
Housing 25 ($)	198485	57094	111500	290500	144508	45350	74500	226500	142164	41327	74000	206000
Housing 50 ($)	276982	86422	166500	406250	223302	83564	111000	419000	222979	71048	115000	352500
Housing 75 ($)	390086	122072	243250	576725	348865	200217	142200	875000	391534	161609	165750	761500

Table B.5. Parameter calibration.: Some parameters of the equilibrium sorting model are calibrated as part of thought experiment whose purpose is to examine the responsiveness of the model to certain parameters. Elasticities for constant price (ω), income (γ), and the CES substitution parameter (ρ) were the focus of this exercise.

Parameter	**Evans (2011)**			**Sieg et al. (2004)**				**Calibrated**
	Model I	Model II	Model III	Model I	Model II	Model III	Model IV	
$\mu_{\ln y}$	10.803	10.809	10.883	10.765	10.782	10.888	10.829	
	[0.015]	[0.013]	[0.042]	[0.038]	[0.066]	[0.051]	[0.035]	
$\sigma^2_{\ln y}$	0.381	0.37	0.326	0.652	0.745	0.69	0.755	
	[-0.008]	[-0.010]	[0.016]	[0.023]	[0.019]	[0.023]	[0.013]	
$\mu_{\ln \alpha}$	0.038	0.059	0.051	0.408	0.833	0.562	0.76	
	[0.004]	[0.006]	[0.007]	[0.191]	[0.172]	[0.229]	[0.199]	
$\sigma^2_{\ln \alpha}$	0.063	0.084	0.071	0.514	0.357	0.492	0.355	
	[-0.001]	[-0.002]	[0.007]	[0.053]	[0.025]	[0.024]	[0.027]	
λ	-0.326	-0.32	-0.309	-0.219	-0.247	-0.247	-0.207	
	[0.005]	[0.004]	[0.023]	[0.058]	[0.097]	[0.097]	[0.029]	
ρ	-0.019	-0.023	-0.021	-0.046	-0.022	-0.03	-0.023	-0.03
	[0.000]	[0.000]	[0.001]	[0.003]	[0.002]	[0.002]	[0.002]	
β	1.39	2.31	1.91	2.909	2.817	2.435	2.971	
	[0.017]	[0.022]	[0.112]	[0.266]	[0.323]	[0.445]	[0.444]	
ω	-0.231	-0.584	-0.411	-0.116	-0.039	-0.019	-0.037	-0.02
	[0.016]	[0.023]	[0.038]	[0.043]	[0.015]	[0.083]	[0.017]	
γ	0.783	0.795	0.774	0.762	0.734	0.752	0.729	0.75
	[0.002]	[0.003]	[0.010]	[0.009]	[0.011]	[0.012]	[0.014]	

Table B.6. Unconstrained parameter estimates.: Parameters are estimated with a one-stage generalized methods of moments (GMM) estimator. Parameter estimates are used to simulate, then sort, households.

Parameter	Casco Bay			Damariscotta River			Penobscot Bay		
	Estimate	Std. Err.	T-statistic	Estimate	Std. Err.	T-statistic	Estimate	Std. Err.	T-statistic
$\mu_{\ln y}$	11.001	0.012	954.960	10.791	0.009	1167.390	10.689	0.014	778.590
$\sigma^2_{\ln y}$	-0.650	0.066	-9.855	-0.526	0.040	-13.205	0.753	0.061	16.456
$\mu_{\ln y}$	0.841	0.113	7.417	0.710	0.734	0.967	1.894	0.626	3.026
$\sigma^2_{\ln y}$	0.112	0.028	4.053	0.347	0.171	2.022	1.074	0.152	5.085
λ	-1.106	0.142	-7.763	-1.746	0.563	-3.102	-0.622	0.361	-6.009
$gknot$	1.833	0.094	19.420	1.100	0.389	2.831	2.426	0.339	7.148
$\gamma_{School\ Quality}$	-0.972	0.178	-5.454	0.182	0.195	0.934	-0.613	0.837	-0.733
$\gamma_{High\ School\ Grad}$	1.614	0.096	16.796	-0.029	0.343	-0.086	1.809	0.540	3.348
$\gamma_{Seasonal\ Homes}$	0.422	0.115	3.668	-1.661	0.423	-3.929	0.984	0.621	1.584
$\gamma_{Urban\ 1}$	-0.201	0.026	-7.871	0.591	0.459	1.287	0.143	0.250	0.569
$\gamma_{Urban\ 2}$	-0.503	0.180	-2.801	0.183	0.367	0.499	-0.103	0.077	-1.347
$\gamma_{Water\ Quality}$	2.692	0.266	10.103	-0.694	0.413	-1.681	-0.708	0.391	-1.811
$\gamma_{Aquaculture}$	-0.103	0.010	-10.076	0.505	0.240	2.108	-0.077	0.073	-1.049
$\gamma_{Coastline}$	0.000	0.001	0.404	0.025	0.006	3.983	0.013	0.011	1.205
ρ	-0.071	0.009	-7.666	-0.079	0.027	-2.906	-0.091	0.031	-2.898
β	4.941	0.242	20.409	3.794	0.696	5.451	2.835	0.530	5.349
η	0.094	0.137	0.685	0.734	0.114	6.412	0.398	0.154	2.578
ν	0.772	0.004	184.440	0.759	0.020	37.568	0.804	0.021	38.596

Table B.7. Constrained parameter estimates.: Most parameters are estimated with a one-stage generalized methods of moments (GMM) estimator. However, elasticities for constant price (ω), income (γ), and the CES substitution parameter (ρ) are held fixed. Values were determined by consulting Sieg et al. (2004) and Evans (2011). Parameter estimates are used to simulate, then sort, households.

Parameter	**Cacso Bay**			**Damariscotta River**			**Penobscot Bay**		
	Estimate	Std. Err.	T-statistic	Estimate	Std. Err.	T-statistic	Estimate	Std. Err.	T-statistic
$\mu_{\ln y}$	10.994	0.014	719.840	10.810	0.013	861.450	10.691	0.010	1045.400
$\sigma^2_{\ln y}$	0.566	0.061	21.840	0.570	0.106	9.983	0.779	0.060	15.102
$\mu_{\ln y}$	0.021	0.626	0.082	0.793	0.550	1.441	4.329	1.207	3.586
$\sigma^2_{\ln y}$	1.305	0.152	12.370	0.948	0.138	5.543	1.349	0.229	6.181
λ	-0.075	0.361	-2.689	-0.290	0.084	-7.365	-0.316	0.133	-5.793
$gknot$	0.158	0.339	0.725	1.982	0.802	2.472	0.232	0.234	0.992
$\gamma_{School\ Quality}$	-1.475	0.837	-0.592	0.999	0.662	1.510	-1.180	1.369	-0.862
$\gamma_{High\ School\ Grad}$	-0.954	0.540	-2.887	-1.194	0.763	-1.564	0.415	0.846	0.491
$\gamma_{Working\ Waterfront}$	3.195	0.621	7.477	0.170	0.124	1.369	-1.015	1.282	-0.792
$\gamma_{Urban\ 1}$	0.622	0.250	4.678	-1.431	1.317	-1.087	0.136	0.174	0.782
$\gamma_{Urban\ 2}$	1.017	0.077	1.634	-0.286	4.132	-0.069	-0.257	2.821	-0.091
$\gamma_{Water\ Quality}$	6.678	0.391	92.510	5.573	0.092	60.378	5.964	0.117	51.022
$\gamma_{Aquaculture}$	-0.369	0.073	-2.264	2.438	4.102	0.594	0.004	0.444	0.008
$\gamma_{Coastline}$	-0.004	0.011	-4.781	0.062	0.023	2.677	-0.017	0.013	-1.282
ρ	-0.030			-0.030			-0.030		
β	9.100	0.530	1.875	10.915	6.861	1.591	-5.224	19.427	-0.269
η	-0.020			-0.020			-0.020		
ν	0.750			0.750			0.750		

Table B.8. Willingness-to-pay estimates.: Willingness-to-pay is estimated in two sets of models. The unconstrained WTP is estimated by models who had all of their parameters generated directly by the data. The constrained models present WTP that is part of a thought experiment geared towards matching expectations and other results in the literature. Willingness-to-pay is presented as a regional mean, aggregated up from individual household level.

	Casco Bay	Damariscotta River	Penobscot Bay
Constrained Partial WTP	-\$53,266	-\$53,303	\$53,135
Constrained General WTP	\$16,009	\$16,128	\$16,176
Unconstrained Partial WTP	-\$56,082	-\$146,580	-\$278,450
Unconstrained General WTP	-\$∞	-\$∞	-\$∞

Table B.9. Community price rank changes.: Changes in community price correspond to changes in relative community quality. The model estimates observed counterfactual data to produce the new community rankings.

Casco Bay			Damariscotta River			Penobscot Bay		
District	Rank	New Rank	District	Rank	New Rank	District	Rank	New Rank
Cape Elizabeth	1	12	Southport	1	8	RSU 07	1	14
Long Island	2	13	South Bristol	2	14	Brooksville	2	12
Yarmouth	3	1	Boothbay	3	2	Islesboro	3	7
Falmouth	4	5	Georgetown	4	1	RSU 28	4	1
Chebeague Island	5	4	Bristol	5	10	RSU 08	5	8
RSU 05	6	9	Nobleboro	6	12	Castine	6	3
RSU 51	7	10	Bremen	7	7	Deer Isle-Stonington	7	5
Portland	8	11	Edgecomb	8	11	Brooklin	8	13
South Portland	9	2	Newcastle	9	3	Penobscot	9	10
RSU 75	10	7	Damariscotta	10	15	Lincolnville	10	9
West Bath	11	3	RSU 12	11	4	RSU 13	11	2
Brunswick	12	8	RSU 40	12	5	Sedgwick	12	11
RSU 01	13	6	RSU 02	13	6	RSU 20	13	4
			Augusta	14	9	RSU 25	14	6
			RSU 11	15	13			

Figure B.1. Boundary indifference illustration (modified from Kuminoff et al. (2013)).: Boundary indifference is a condition necessary to induce sorting in an equilibrium sorting model. It states that given a continuum of households, there to be households with given taste and income that are indifferent between communities *j* and *j+1,* which are adjacent in relative price.

Figure B.2. Household sorting (modified from Epple and Sieg (1999) & Evans (2011)).: Households a, b, and c are sorted into communities C_1, C_2, and C_3. Community C_1 has the lowest quality and C_3 has the highest quality. Household a holds the lowest income but still sorts into the community of the highest quality because it holds the strongest preferences over the public good. Household c sorts into C_1 despite having the highest income because it holds the weakest preferences over the public good. This example is illustrative of how a household's community choice is jointly determined by preferences for the community-specific amenities and income.

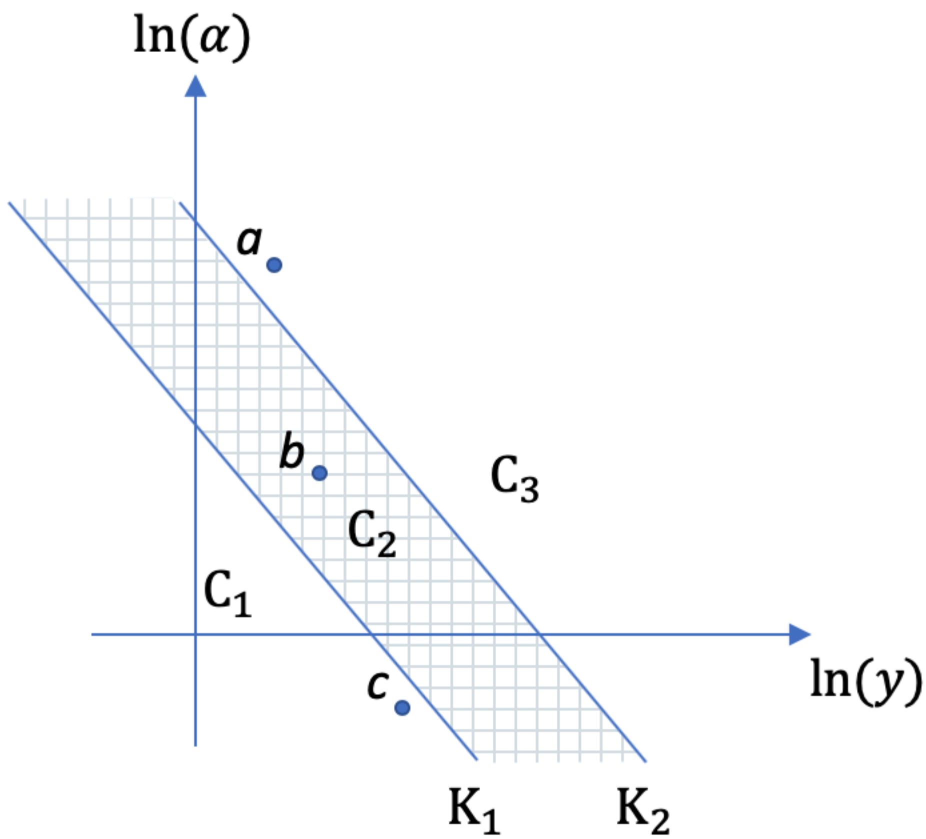


Figure B.3. Study area by region.: There are three distinct and adjacent regions for which willingness-to-pay is estimated: Casco Bay (blue), Damariscotta River Region (red), and Penobscot Bay (red). Within each region, communities are considered substitutes for one another. The inlay map describes where these regions fall within the broader context of Maine's coastline.

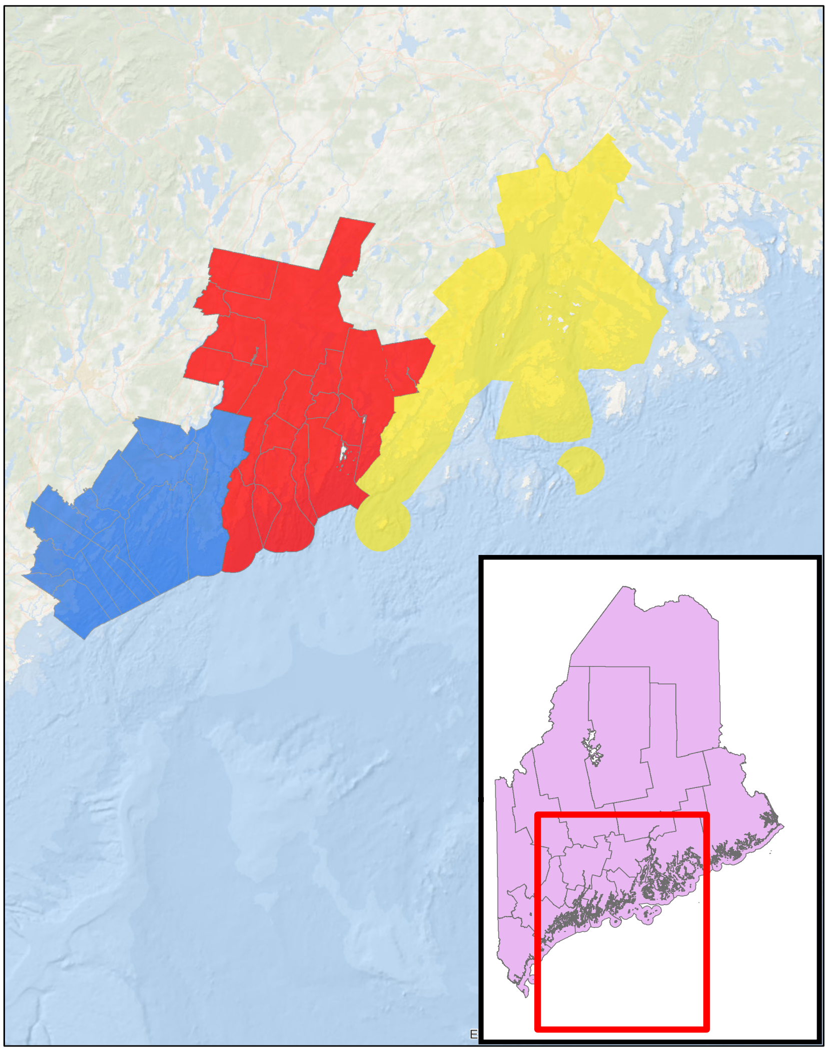


Figure B.4. Casco Bay rank changes.: Changes in community price rankings can demonstrate how changes in aquaculture might benefit or harm homeowners in any given community. Communities shaded the darkest will benefit the most from expanding aquaculture and communities shaded the most lightly are harmed the most. Each community's *change* in relative price is marked.

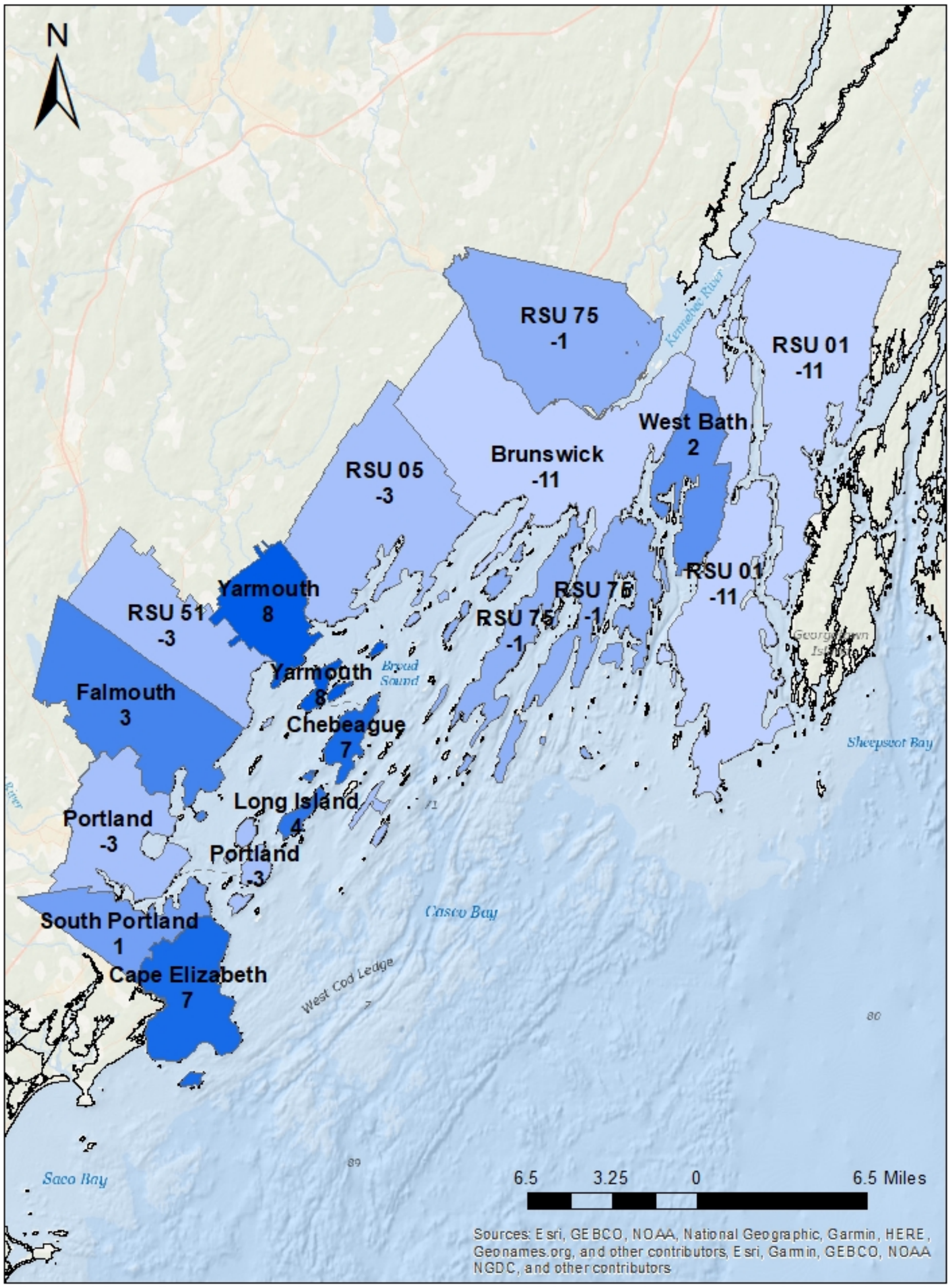


Figure B.5. Damariscotta River region rank changes.: Changes in community price rankings can demonstrate how changes in aquaculture might benefit or harm homeowners in any given community. Communities shaded the darkest will benefit the most from expanding aquaculture and communities shaded the most lightly are harmed the most. Each community's *change* in relative price is marked.

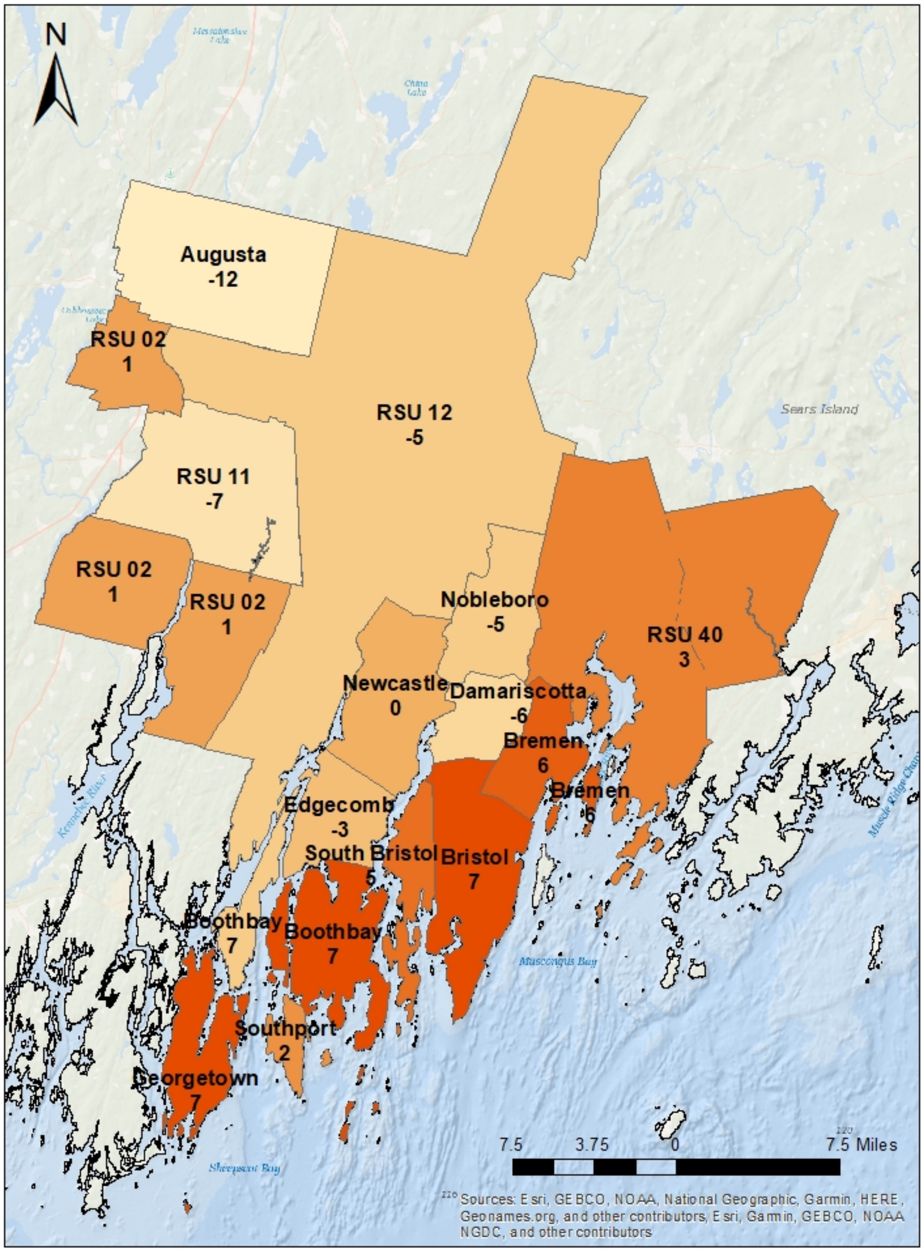
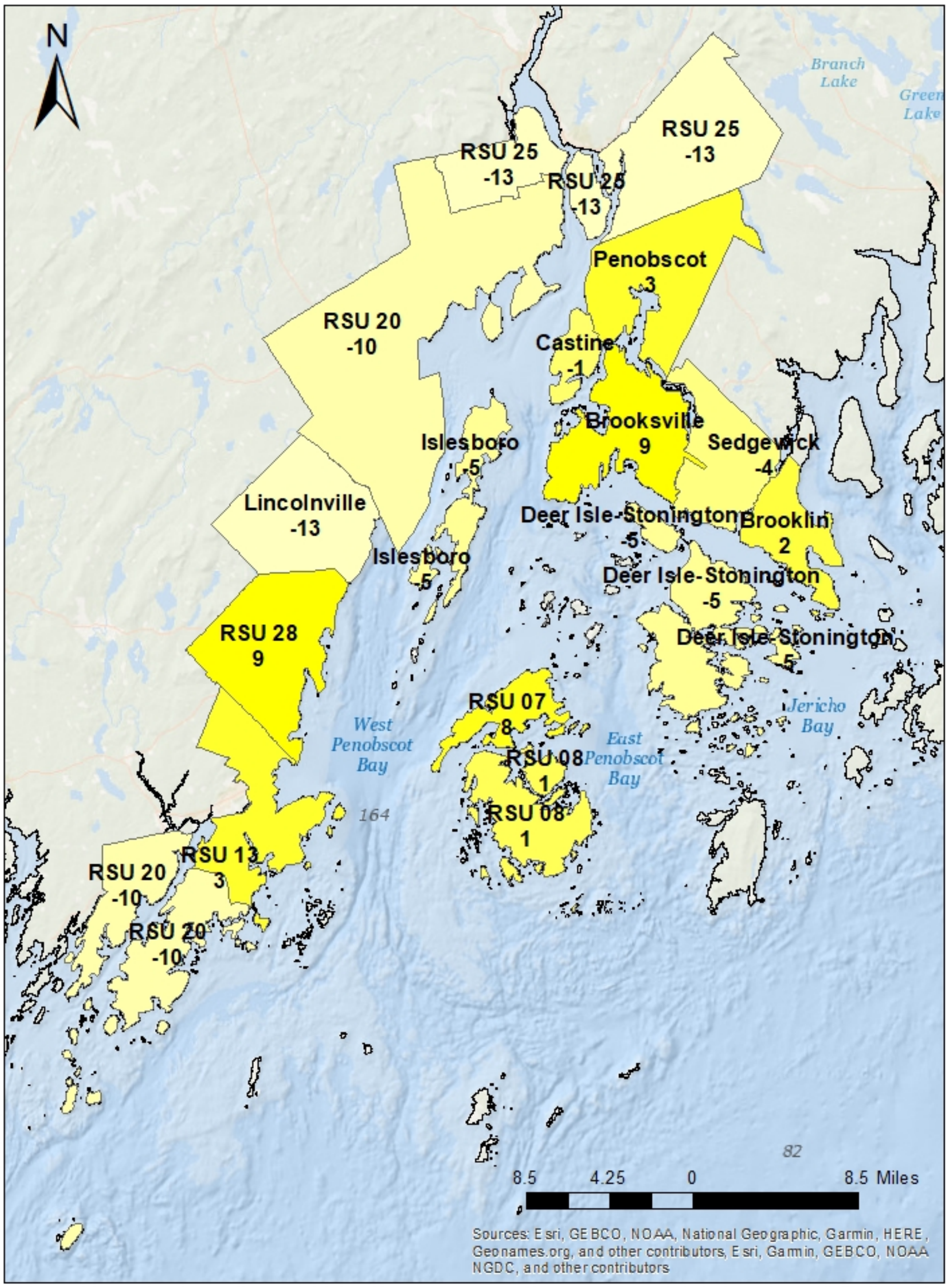


Figure B.6. Penobscot Bay rank changes.: Changes in community price rankings can demonstrate how changes in aquaculture might benefit or harm homeowners in any given community. Communities shaded the darkest will benefit the most from expanding aquaculture and communities shaded the most lightly are harmed the most. Each community's *change* in relative price is marked.



BIOGRAPHY OF THE AUTHOR

Avery Cole was born in Bangor, Maine on September 22, 1993. He was raised in Orono, Maine and graduated from Orono High School in 2011. He attended the University of University of Connecticut before transferring home to the University of Maine, where he graduated in 2016 with a Bachelor's degree in Political Science. He began his work with aquaculture at the Aquaculture Research Institute, where he designed, distributed and analyzed economic impact surveys focused on Maine's industry. After a year spent bartending and traveling, he returned to Maine and entered the Economics graduate program at The University of Maine in the fall of 2017. After receiving his degree, Avery will be joining DNV GL., an international maritime and energy consulting firm, to begin his career in the field of energy consulting. Avery is a candidate for the Master of Science degree in Economics from the University of Maine in August 2019.