

2015

Reputation Effects and Hedonic Pricing at the Portland Fish Exchange

Kush Jadeja
Colby College

Follow this and additional works at: <https://digitalcommons.colby.edu/honorstheses>



Part of the [Economics Commons](#)

Colby College theses are protected by copyright. They may be viewed or downloaded from this site for the purposes of research and scholarship. Reproduction or distribution for commercial purposes is prohibited without written permission of the author.

Recommended Citation

Jadeja, Kush, "Reputation Effects and Hedonic Pricing at the Portland Fish Exchange" (2015).
Honors Theses. Paper 782.
<https://digitalcommons.colby.edu/honorstheses/782>

This Honors Thesis (Open Access) is brought to you for free and open access by the Student Research at Digital Commons @ Colby. It has been accepted for inclusion in Honors Theses by an authorized administrator of Digital Commons @ Colby.

Reputation Effects and Hedonic Pricing at the Portland Fish Exchange

Written By: Kush Jadeja

Senior Economics Honors Thesis

Spring 2015

Advised By: Professor Randy A. Nelson

Abstract

The Portland Fish Exchange, founded in 1986, is America's first all-display fresh seafood auction. The ability to observe each lot of fish before it is sold enables buyers to offer prices that reflect the perceived quality of the fish they bid on. As a result, the price per pound paid for lots of identical fish can vary significantly on any given day, implying that some boats or sellers may benefit from a "reputation" effect for high quality fish. In this study I explore the factors that explain the price differentials paid for a given type of fish using data from the PFEX over the period 2009-14. Controlling for the type of fish, the day, month, and year in which the lot was sold, the weight of the lot, the buyer, and the total amount of fish sold on a given day, I attempt to explain the reputation effect using both a boat fixed effects model, and a model that controls for the type of gear used to catch the fish, the length of vessel, and the length of the trip. I attempt to determine if the reputation effect is stable over time, and if it is related the cumulative number of landings for a given boat, which measures the degree of familiarity a buyer would have with a given seller.

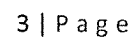
Section I: Introduction

Prior to the founding of the Portland Fish Exchange (PFEX) in 1986, there was little incentive for fishermen throughout New England to focus on improving the quality of the fish they sold to their customers. In the three major fishing ports in Massachusetts, Boston, New Bedford, and Gloucester, buyers never saw the fish they purchased until they took physical possession of the fish. In Gloucester fishermen established long-term relationships with buyers, agreeing to sell their fish at mutually agreed upon prices that were based on prices at other fishing ports throughout New England. In New Bedford buyers would agree to purchase all of the fish landed by a given boat without being able to see the fish, often times obtaining species or sizes of fish for which they had little interest. In Boston buyers would bid on all of the species landed by a given boat, thus avoiding taking other unwanted sizes or species. In every case, however, the buyer bought the fish “sight unseen”, thus providing fishermen with little incentive to improve the quality of their catch.

The PFEX was the first all-display auction to open in the United States, although all-display auctions have existed in Europe and Japan for decades. The PFEX represents a “neutral market” in the sense that it is not owned by the buyers or sellers; the PFEX obtains its funding from fees received from the buyer and seller on each lot of fish sold, from services such as processing, storage, and shipping, and from revenue from the State of Maine and the City of Portland. The PFEX provides over two million pounds of fish annually to twenty-two different buyers, who in turn provide fish not only to the majority of local fish stores and restaurants throughout Maine, but also to fish wholesalers and processors who fish throughout the Northeast and the entire United States.

Between 2006 and 2014 one hundred and ten fishing boats landed fish at the PFEX, although only seventy boats did so on a regular basis. The boats land their fish in the evening before they are auctioned, or early in the morning before the auction begins at 11 am. Workers at the PFEX sort the fish by species, size, and boat into lots that contain anywhere from one pound to 1,200 pounds. Each lot contains only a single species, Cod for example, and are further divided by size, large, medium, or small. Each lot of medium or market Cod, for example, is boat specific – the same size and species of fish from one boat are never mixed with fish from another

Figure 1



The focus of this study is to explore, and hopefully understand, why the prices of different species and sizes of fish vary by year, month, and day, and in particular whether or not different boats systematically receive higher or lower prices for the fish that they sell; ie., whether or not boats develop reputation effects that lead to price differences across sellers. The statistical models are estimated using a panel data set containing over 70,000 observations obtained from the PFEX covering the period 2009-2014. The models control for year, month, day, species, and seller fixed effects, and allow for the estimation of price differentials across boats controlling for these factors. Further analysis is then undertaken to determine what role, if any, the type of gear employed by a boat and the length of fishing trip they undertake, play in determining the price they receive for their fish. In addition, for a sample of boats I explore whether or not these reputation effects are stable over time. Finally, I study whether or not the number of interactions between buyers and sellers, as measured by the number of times a boat lands fish at the PFEX, affects the price they receive for their fish over time.

Section II: Literature Review

Authors in the discipline of economics have previously studied fish markets similar to the Portland Fish Exchange. Kathryn Graddy (2010) studied the daily supply and demand for Whiting fish at the Fulton Fish Market. This study only analyzed the prices and related movements of one type of fish and a single dealer. In my study, I look at multiple species of fish and focus more on the sales of multiple dealers and combining the values based on fish type and size. Thus allowing me to examine possible reputation effects and continuity of these effects over time. Graddy, on the other hand, knew nothing about the boats or sellers in her sample and was simply looking at the shifts in supply and demand for Whiting.

Like this study, Graddy also uses aggregate data and thus requires some sort of control for the endogeneity derived from using total data. Graddy also shows that simply using OLS would result in biased estimates for our coefficients and thus demonstrates the necessity to use instrumental variables to correct for the potential bias. The methodology of Graddy's study assumes that the weather variable of wind speed enters the supply equation and will presumably have no effect on the demand for fish, thus making it a supply shifter. Graddy states that a high wind speed will suppress quantities of fish supplied and increase prices for this fish just as one would expect from an inward shift of the supply curve. The basic concept behind the

instrumental variables approach is to use these variables to take advantage of movements in price that are caused by shifts in the supply curve and are not systematically related to the demand curve. Thus, movements in price that are caused by shifts of the supply curve can be used to trace out a demand curve and are not correlated with our error term that remains heteroskedastic. Some of the points of curve in this situation represent shifts by both the demand and supply curve. Using instrumental variable methods can separate out the parts of movement between points that can be explained only by shifts in the supply curve.

Graddy uses this estimation technique to derive the demand for Whiting at the Fulton Fish Market. Murray et al. also show that 2-Stage Least Squares can be used to estimate and over identified equation. This is a method that combines multiple instruments in order to take advantage of all of the movements in price that can be attributed to shifts in the supply curve, using all available supply shifters. I utilize this methodology to use the weather data from the surrounding area of the Portland Fish Exchange to develop instrumental variables.

In order to estimate the demand curves that are involved in the price of fish, the literature has found two methods to properly evaluate these. The first is estimating system of demand curves and thus be able to find cross-price elasticity's of demand for various fish. Given our data set, I would have to look at multiple fish species. The demand for Cod, for example, may depend on the price of Haddock given that the two can be seen as substitutes. By estimating multiple demand curves one can derive a demand function based on all prices given. Another possible approach to estimating these demand curves is using a hedonic method to find the demand. On a given day, for a given size and type of fish, I can find the difference in amount paid for particular lots. These differences can then be analyzed using the instrumental variables approach outlined earlier. Combining that methodology with the hedonics approach I can find the prices that different sellers get based on their boat.

In this setting, hedonic regressions have also been used for studying the fish market. Examples include McConnell and Strand (2000), Carroll et al. (2001) and Lee (2014). These have all looked at how quality characteristics, including freshness, affected the price of various species of fish in their respective markets. Kristofersson and Rickertson (2004) mixed a hedonic regression approach with an inverse demand model to study the effect of quantity changes in difference size categories on the price of Cod. They also used hedonic analysis (2007) to

examine the demand for Icelandic cod characteristics; size and freshness are both associated with higher prices. The first attempt of the hedonic model was first described by Rosen (1974), has often been used to examine the implied price of characteristics of heterogeneous goods.

This same methodology was first utilized to study fish by Larkin and Sylvia (1999) on surimi. Ironically, this is also a product of Pacific whiting and other species. For whole fish sales, size and quality are frequently associated with higher prices. Asche and Guillen (2012) find that country of origin, fishing gear and size all determine prices of Hake in Barcelona's wholesale market. McConnell and Strand (2000) examined hedonic pricing for the wholesale Hawaiian auction market for tuna. These authors found that grade and species account for a very large portion of the variation of prices and fishing gear explained only a small amount of variation in prices.

As shown above these hedonic regressions have been used extensively throughout the literature and give a strong framework to look forward from. A more specific and similar example to my work is Min-Yang Lee's work on Hedonic Pricing of Atlantic Cod (2014). Lee looks at the effects of size, freshness and gear in the development of prices for certain types of Cod in the Atlantic. She uses this hedonics method to model and estimate cod prices in the northeast U.S. and found that grade and species accounted for a very large portion of the variation in prices and that fishing gear explained only a small amount of variation in prices. Lee used sales data taken from the NMFS's mandatory dealer reporting records with the trip-level characteristics extracted from NMFS's mandatory Vessel Trip Report database to develop this estimation. She then combined the observations with identical values of these four characteristics into a single sale and weighted the average prices used. These coefficients for the continuous variables can be interpreted as the effect of a change of that variable on price.

Lee only used a single species but divided the species into 6 major categories. In our data, I use different species and size categories to separate our data. In this example, Lee does not look at weather as a variable for catch, which is an important improvement in our study. The author also studied concepts of freshness, including trip duration, and the difference between landed date and sold date. Lee found that gillnet-caught cod always received the lower price and the longline- and trawl-caught cod always receive higher prices. Lee also found freshness to be a determinant of price. Cod stored for longer days received a price penalty ranging from \$0.05 -

\$0.10 depending on how many days it has been stored for. These price signals, if they exist could create incentives for fishermen to adjust fishing practices by changing gear, reallocating effort, or targeting particular sizes. This could be a possible determinant of the reputation effects I am trying to study.

I will be using these ideas as well as other variables to discuss the idea of reputation and why some boats in our data set consistently receive higher prices for their catch. It is important to note that this study differs from all others in the literature because the focus is on the boats or sellers rather than on a specific type of fish. In addition to this, Lee uses the hedonic model to assess the bioeconomic models whereas I am looking more closely at the economic price effects.

Section III: Data Summary

The Portland Fish Exchange (PFEX) was originally initiated by the seafood sellers looking to benefit from landing high quality fish, the unprecedented approach of displaying a catch after offload and prior to purchase was a success for both buyer and seller. Previously, buyers had to simply buy a boatload catch before the vessel even docked, with this new system the best quality fish were rewarded with higher prices and thus led to the benefits of the exchange. The Portland Fishing Fleet is not a conglomerate of international boats but is an intimate group of fishermen in smaller vessels with a commitment to fishing and living in Maine. The fleet currently consists of approximately 70 vessels that may be classified as trawlers, who drag funnel-shaped nets behind their boats, or gillnetters, who deploy long nets in a fixed position to catch their fish. The boats that land at the PFEX make either short “day boat” trips or longer multi-day trips to sea, generally depending on the size of the boat. Although the core fleet is only 70 boats, boats enter and exit the fleet and any boat is welcome to sell at PFEX.

The exchange upgraded to a computerized trading system on March 10, 2009 and has collected data in that manner since then. The data provides daily information from the exchange for the time of the system upgrade through to September 30, 2014. The data set originally contained 144,741 observations over the 6-year period. In this data set an observation is a lot of fish, where (i) each lot contains fish from only one boat, (ii) each lot contains only a specific type and size of fish, and (iii) the size of the lot can vary from one pound to over 1,200 pounds.

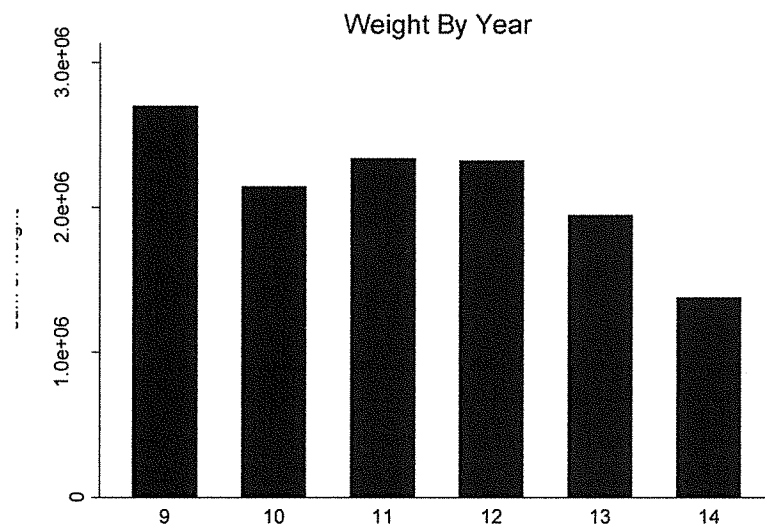
The initial data set covered 104 different items, where an item in our data set is lot of a type of fish of a given size, for example, large cod, market cod, or scrod (small) cod. (scrod, market, etc). It is important to note that in this study does not examine aggregate data (i.e. the total amount of a fish sold on a given day) but rather looks at the exact price and weight of a specific lot size of a particular species. Many of the items in the original data had a limited number of observations; for example, the Small Georges Blackback and the Windowpane Mixed Flounder had only one lot sold over the entire 6-year period. In an effort to focus on the most substantial items, I focused only on items that had at least 1,000 lots. In every case but one, these lots represented at least 1% or more of the original sample. By doing this I reduced our sample to 23 unique items and discarded 6,117 observations, leaving 95.77% of the original sample. Additionally the exchange has some lots that do not get sold; these lots do not have price data available and thus are not useful to the study, which deleted an additional 4,546 observations from the data sample.

A primary focus of this study is to explore why the price of a given type and size of fish can vary on a given day. Past research by Lee (2014) shows that the type of gear used to catch the fish and the length of the fishing trip impacts the price paid for fish. It was possible to collect data on gear type and trip length for a subset of the original data set from researches working at the Gulf of Maine Research Institute. In order to finalize the data set I drop observations that lack data on the type of gear (49,383) followed by additional observations for lack of data on length of trip (14,049). After a thorough cleaning, the final sample contained 70,646 observations that represent 48.81% of the original sample.

The amount of fish sold at the PFEX varies by year, month, and day of the week. The total amount of fish sold each year at the PFEX is shown in Figure 2. Although the data begin in March of 2009, the total amount of fish sold that year exceeds the amount sold in any other year. Part of the decline in 2010 may be due to the change from a trip based to quota based regulatory scheme that began in May of 2010. It should be noted that the data for 2014 end on September 30, implying that the total for that year was greater than that shown in the graph.

Table 1: Summary of total weight by year.

Year	N(weight)	mean(weight)	sd(weight)	sum(weight)
2009	14,336	188.24	270.13	2698553
2010	10,368	206.82	279.85	2144277
2011	13,427	174.01	243.40	2336422
2012	13,405	173.14	250.00	2320934
2013	11,074	175.92	260.51	1948155
2014	8,036	171.76	267.08	1380293

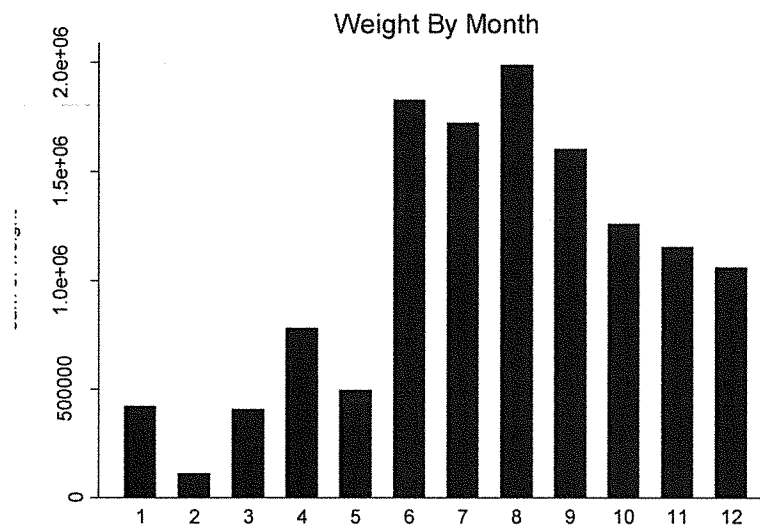
Figure 2

The total amount of fish sold each month over the course of the 6 year period is shown in Figure 3. The summer and early fall months clearly have higher catches than the winter months, this is likely due to more favorable fishing conditions. I see a depression in May due to the quota enforcement laws that came into effect in 2010. These results show that having a lot of fish sold in a given month may in fact affect the price a seller receives for their fish based on a supply side story.

Table 2: Summary of total weight by month

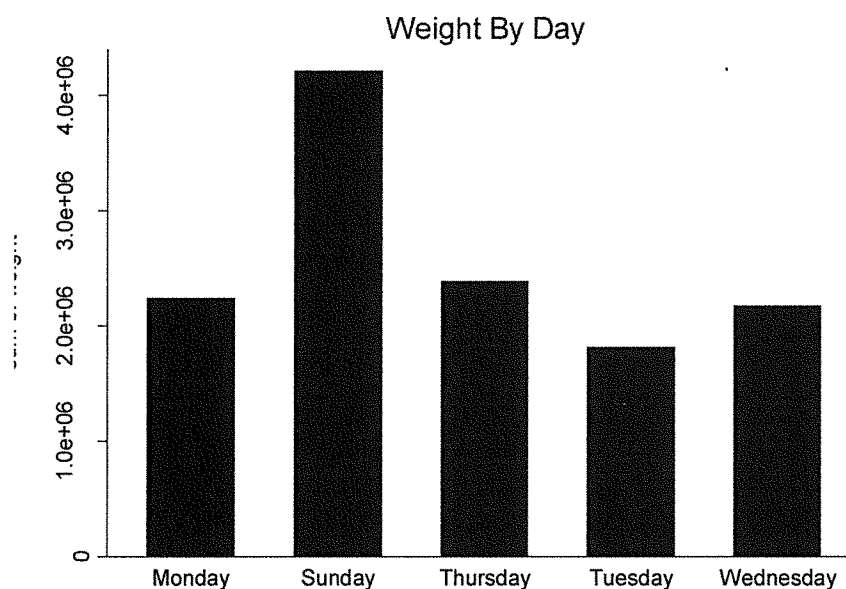
Month	N(weight)	Mean(weight)	SD(weight)	Sum(weight)
January	1,410	299.50	325.52	422301
February	383	291.08	337.31	111485
March	1,499	271.46	336.08	406924
April	4,274	183.05	281.85	782343
May	2,947	168.08	235.31	495328
June	12,078	151.38	228.87	1828352
July	13,239	130.08	194.68	1722164
August	12,689	156.59	230.78	1986964
September	9,137	175.39	245.04	1602554
October	5,803	217.10	287.46	1259814
November	4,086	281.98	342.74	1152185
December	3,101	341.25	370.08	1058220

Figure 3



The daily distribution of lot weight also shows a similar pattern. As shown in Figure 4, there are significant daily swings in the number of fish sold. This is especially true on Sunday, due to the fact that the exchange is closed Friday and Saturday. This influx of fish on Sundays could potentially depress the price received by sellers for multiple reasons: one reason being the supply side story mentioned earlier, and the second reason being a freshness factor. The fish sold on Sunday may have been caught on Friday and thus would be less fresh and command a lower price.

Figure 4: Distribution of Total Weight by Day

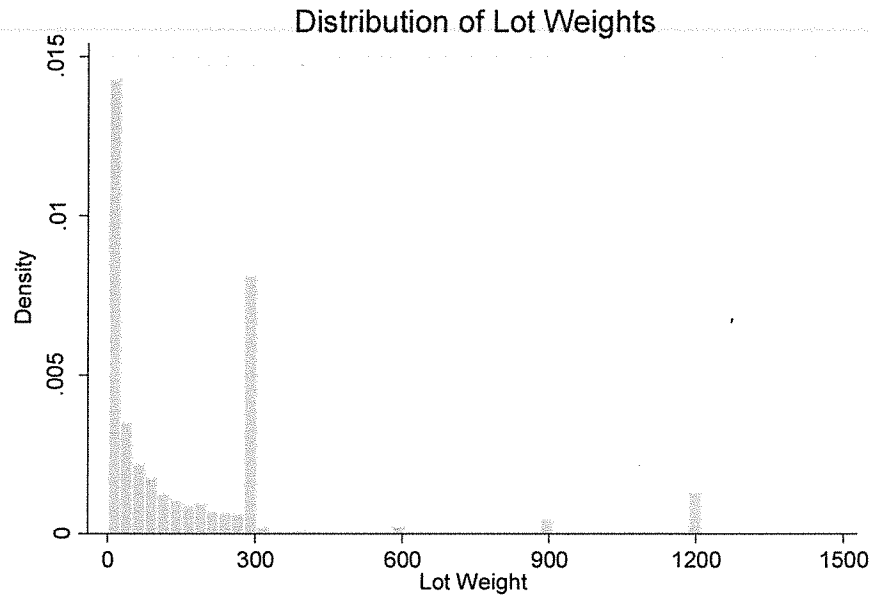


Our data manipulation left us with 23 unique items. These unique items are shown below in Table 3, there are 10 unique species of fish broken down into various size categories. Shown in Table 3, are the frequencies of these items caught and a total of the amount of items (70,646). Although the total number of unique items has shrunk considerably I am still left with approximately 50% of the total landings over our time period thus this specification does not detrimentally affect our sampled. When looking at this group of items I see that some items have less than 1000 observations. Although this contradicts what was stated above, the cut down in the number of items was based on the original sample not the smaller sample that has reduced observations based on price data and type of gear.

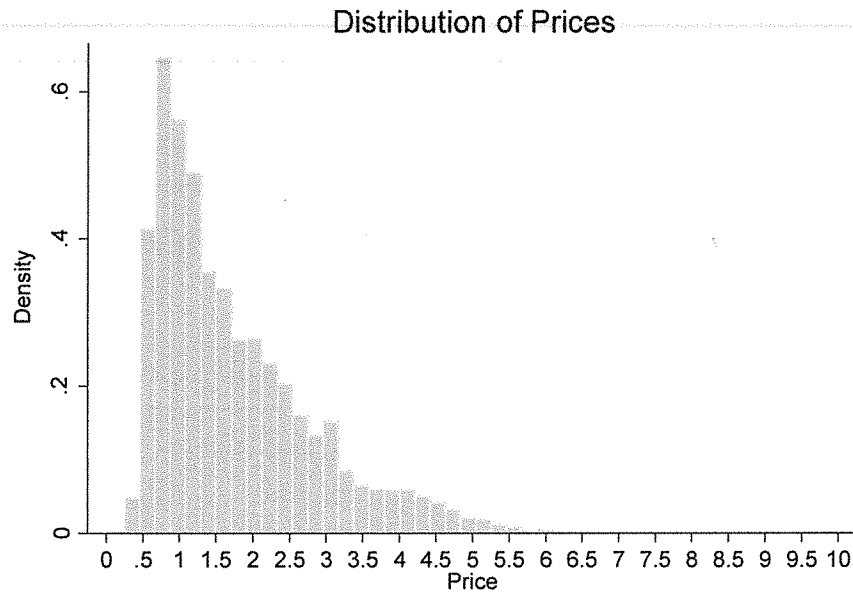
Table 3: Breakdown of All fish by species and size

ITEM, SIZE	FREQ	PERCENT	CUM.
Cod, large	4,293	6.08	6.08
Cod, market	6,994	9.90	15.98
Cod, scrod	831	1.18	17.15
Cusk, mixed	1,739	2.46	19.61
Dab, large	760	1.08	20.69
Dab, medium	1,213	1.72	22.41
Dab, small	2,510	3.55	25.96
Greysole, large	356	0.50	26.46
Greysole, medium	850	1.20	27.67
Greysole, small	2,053	2.91	30.57
Haddock, large	1,047	1.48	32.06
Haddock, scrod	1,470	2.08	34.14
Hake, white large	6,160	8.72	42.86
Hake, white medium	3,346	4.74	47.59
Hake, white small	1,586	2.24	49.84
Hake, white sow	1,637	2.32	52.15
Monkfish, tails large	3,877	5.49	57.64
Monkfish, tails small	3,101	4.39	62.03
Pollock, Atl large	10,102	14.30	76.33
Pollock, Atl medium	7,571	10.72	87.05
Pollock, Atl small	4,789	6.78	93.83
Redfish, mixed	2,756	3.90	97.73
Whiting, mixed	1,605	2.27	100.00
Total	70,646	100.00	

As stated earlier, our unique unit of observation in this case is a lot of fish. These lots come from individual boats and can be comprised of a variety of weights. Boats that are fishing primarily for cod may land a single dab as “bycatch”, and that one fish would constitute a lot of perhaps one pound. As a result, the size of a lot can range from 1 pound to over 1,200 pounds. Figure 5 shows the distribution of lot sizes by weight. This histogram shows that the majority of lots are very small in size. The spikes that occur at 300 pounds, 600 pounds, 900 pounds and 1200 pounds occur because commercial processors tend to purchase lots in those increments.

Figure 5

The price variable represents the price paid per pound of fish, and not the price of an entire lot. For our sample the average price is \$1.75 with a standard deviation of \$1.11. Additionally, as shown in Figure 6, there is a wide range of prices (ranging from <\$1 to >\$10) for our full sample of 70,646 observations. The price per pound could vary for a number of reasons. First, different species of fish command different prices; the average price per pound of monkfish tails is \$4.04, while the average price per pound of small hake and whiting is \$.77. Another possible reason for the large array of prices could be the variance in lot sizes, as there could be a discount for buying a bulk sized lots rather than one of the more typical small lot sizes. Additionally, buyers may have different elasticities of demand depending upon the ultimate use of the fish. Some buyers purchase only the best fish for resale to local restaurants and other fish dealers, while others purchase fish for commercial processing. Finally, a large piece of this paper looks at seller's quality of fish. Prices could vary by seller even if it is for the same lot of fish because a certain seller has the reputation of a higher quality of fish.

Figure 6

In this reduced data set I have a total of 22 separate buyers. Within this there are a few buyers, including Channel Fish Processing Company and Legal Seafoods that buy a very limited amount of fish and there is an even smaller number that have dropped out of the exchange. A full breakdown of buyers can be seen in Table 4 shown below. A study of the buyers shows that there are buyers that pay particularly high prices for fish. There are two examples of this, Browne Trading Company and Harbor Fish Markets, INC.. Both of these companies are Portland based distribution companies that deliver the fish bought from the market to high-end restaurants in the greater Portland area. These two buyers often pay inflated prices due to their clientele often demanding the highest quality of fish.

Table 4: Breakdown of Buyers

Buyer	Freq.	Percent	Cum.
Ad-Jon	5,435	7.69	7.69
Annabelle Lee Inc/Smitty's	13,654	19.33	27.02
Bristol Seafood, Inc.	2,846	4.03	31.05
Browne Trading Company	3,204	4.54	35.58
Channel Fish Processing Co.	2	0.00	35.59
Cozy Harbor Seafood	3,167	4.48	40.07
Douty Brothers, Inc.	1,290	1.83	41.90
Emerald Seafood	2,976	4.21	46.11
Freedom Fish LLC	6,730	9.53	55.64
Great Eastern Seafood, Inc.	4,854	6.87	62.51
Harbor Fish Markets, Inc.	5,409	7.66	70.16
Legal Seafoods	35	0.05	70.21
M.F. Foley, Inc.	1,200	1.70	71.91
North Atlantic, Inc.	723	1.02	72.93
Nova Seafood, LTD.	6,285	8.90	81.83
P.J. Merrill Seafood, Inc.	657	0.93	82.76
Red's Best	413	0.58	83.35
Sea Fresh U.S.A Inc.	621	0.88	84.22
Sea Salt, LLC	2	0.00	84.23
Sebasco Wharf	849	1.20	85.43
Smitty's Fillet House, Inc	1,718	2.43	87.86
Tri-State Seafoods , Inc.	8,576	12.14	100.00
Total	70,646	100.00	

The sellers (boats) on the other hand provide an interesting story that I study further throughout this paper. The initial sample contained 110 vessels but, after restricting to only those boats for which I was able to obtain data on the type of gear employed and the length of trip, only 27 boats remained. A number of the boats that were eliminated landed fewer than 100 lots of fish at the PFEX, and in some cases only sold fish at the auction on a single occasion. The frequencies of lots for boats are shown in Table 5. It is important to note that the frequencies are for lots of fish not pounds or number of landings. Of the 28 total boats in our reduced sample, I see that the boats Heidi & Elisabeth and Safe Haven account for over 25% of total lots sold.

Table 5: Breakdown of Sellers

Seller Name	Freq.	Percent	Cum.
American Heritage	586	0.83	0.83
Black Beauty	17	0.02	0.85
Bridget Leigh	55	0.08	0.93
Free Bird	3,812	5.40	6.33
Gulf Venture	1,838	2.60	8.93
Hannah Jo	5,848	8.28	17.21
Harmony	431	0.61	17.82
Heidi & Elisabeth	11,319	16.02	33.84
High Roller	1,272	1.80	35.64
Jeanne C	1,421	2.01	37.65
Lady Mae	521	0.74	38.39
Lauren Dorothy 2	1,187	1.68	40.07
Leslie & Jessica	775	1.10	41.17
Maria & Dorothy	4,628	6.55	47.72
Marion J	6	0.01	47.73
Miss Maura	5	0.01	47.73
North Star	447	0.63	48.37
Pamela Grace	6,581	9.32	57.68
Pretender	2,163	3.06	60.74
Rachel T	4,406	6.24	66.98
Rolling Stone	2,550	3.61	70.59
Safe Haven	7,707	10.91	81.50
Sara Gale	2,606	3.69	85.19
Shannon Kristine	4,131	5.85	91.03
Sweet Misery	11	0.02	91.05
Teresa Marie 4	463	0.66	91.71
Teresa Marie III	819	1.16	92.86
Theresa Irene	5,041	7.14	100.00
Total	70,646	100.00	

Another aspect of this data set is the boat characteristics available for all sellers at the exchange. As discussed earlier, one possible determinant of price could be the type of gear used. In our original sample I had boats that used three main types of fishing gear. These were trawl, trawl purse, and gillnet. Previous literature has shown that type of gear used or the “method” of fishing can cause differentials in price. (Lee 2014) Thus in an effort to find a potential pattern I analyze the different types of fishing methods for the 28 boats in our final sample. Our final sample only includes boats that have trawl nets and gillnet because there was only one boat in

the entire sample who used trawl purse gear (this boat also did not have vessel length data and was removed for those reasons as well). Additionally, the data provided has another possible boat characteristic that could lead to differentials in price. Boats at the exchange either go on day trips or multi-day trips. It has been shown in other studies that trip length can be a measure of freshness and thus, boats who take longer fishing trips could potentially have older, less fresh fish and thus receive a lower price for their individual lots. In order to test the relationships between these various boat characteristics I use a t-test to analyze whether average boat length was the same for boats that used different types of gear, and for boats that took multi-day trips versus first day trips. A t-test on both of these two comparisons are both rejected and show that the average boat length for boats that use gillnet is different than the average boat length for boats that use trawls. The null hypothesis was also rejected for the test on trip length, showing that average boat length for multi-day fishing boats was different than the average boat length for day trip fishing boats. A two-way classification table shows that most gillnetters do day trips and most trawlers do multiday trips. (See Table 6 for specific breakdown of boat characteristics)

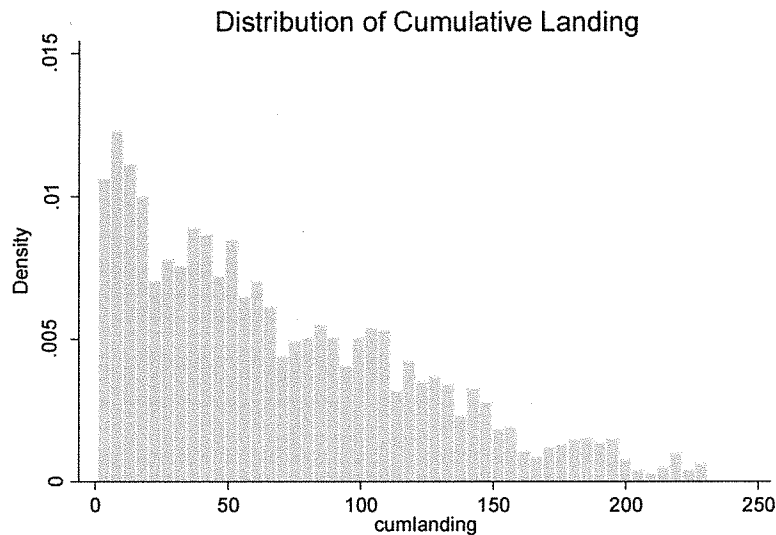
Table 6: Breakdown of Gear Type and Length of Trip

Trip Length	Gear Type		Total
	Gillnet	Trawl	
Day	13	4	17
Multi Day	4	7	11
Total	17	11	28

A final determinant of price is the variable of cumulative landings. In our dataset this variable is coded as “*cumlanding*”, this variable is made up of all the landings made by a single boat at the PFEX over the course of the data set. This variable could be a possible first look into the reputation effects for each of the boats. A priori it is difficult to determine the nature of the relationship between the number of cumulative landings and the price received per pound of fish. Boats that initially receive a higher price may choose to continue landing fish at the PFEX, implying that a high price causes a higher number of cumulative landings. On the other hand, it may be easier for buyers to determine the quality of fish for boats that land frequently at the PFEX, implying that higher cumulative landings lead to higher fish prices As shown in Figure 7, I see that many boats never get to more than 100, 150 or more landings. Thus the boats with the

high cumulative landings would possibly be the boats that receive the highest prices for their lots of fish. This is one of the main outcomes explore in a later section of this paper.

Figure 7



The final component to the data set is our weather variables. The weather data is daily weather data from Station 44031, Buoy E01, Central Main Shelf. This data was available every 10 minutes. The data has been sorted and I have kept only the observations at 6:00 am each day for consistency. The data includes Air Temperature, water temperature at varying depths, wave height, wave period, wind gust and speed. For a few gaps, I use data from Buoy 4407 to fill the gaps in data from Buoy E01. Buoy 4407 is located 12 nautical miles to the south east of Portland. The majority of this data will be used as a proxy variable for the total weight variable in our two-staged least squares equation. Due to the fact that some boats go out for day trips and other boats go out for multiple day trips I created three day averages for the three key variables. These were atmospheric pressure (atmospres), wave height (waveheight), and wind gusts (windgust). The higher the atmospheric pressure the better the days' catch is likely to be whereas the higher the wave height and stronger the wind gust the worse the days' catch will be. See Table 8 for a breakdown of the relevant weather variables.

Table 7

Variable	Obs	Mean.	Std. Dev	Min	Max
atmos13	70646	1014.52	5.93	989.93	1034.98
wav13	70646	3.09	1.36	0.76	14.47
wndgst13	70646	12.06	5.24	2.67	34.33

Section IV: Methodology

In this paper I wish to explore the determinants of the price of a given lot of fish on the Portland Fish Exchange. The price of a given lot of fish will depend on a variety of things. First, it will depend of the type of fish. As shown in Table 3, I have 22 different types of fish in our sample. Unique species in our sample these are: Cod, Cusk, Dab, Greysole, Haddock, Hake, Monkfish, Atlantic Pollock, Redfish and Whiting. Depending on the type of fish, the price could fluctuate based on the availability of its substitutes, supply available and current market demand of the fish. All of these possibilities must be taken into account. In addition, it is hypothesized that the larger fish of a given species will command a higher price because they provide fish cutters with a higher yield.

A second dependent variable is the day of the week, because the exchange is closed on Fridays and Saturdays any fish caught during these days is auctioned on Sundays. The larger quantity may depress the price given excess supply, but this effect could be diminished given that Sunday also attracts the most buyers thus heightening demand for fish. Thursday prices may also be inflated due to the closure of the exchange on Friday and Saturday, buyers may be attempting to stock up or receive the last remaining lots of fish before losing fish availability for the weekend.

A third potential determinant is the month of the year that the fish are being auctioned. Seasonal fluctuations in weather patterns can often affect boats abilities to catch fish. As shown in our data, May often has a low total catch because, as stated earlier, fisherman's permits often expire in May and thus many boats have already met their quota by this month and thus can't catch any more fish. The summer and early fall months tend to have the highest average weight over the year and thus could depress prices. Migratory patterns of fish also vary throughout the year, this makes it easier or more difficult for boats to catch at different times of the year.

Additionally, I control for the year in which the fish was sold, thus allowing us to control for year to year changes in unobservable variables that remain constant during a single year but could change from year to year. An example of this is regulations and restrictions on fish change on a yearly basis and thus could affect the catch of fish as well as the price.

A fifth determinant is the buyer of the lot of fish or participants at the auction. Some buyers purchase only the highest quality fish for resale to high-end restaurants and other fish stores. These buyers have much less elastic demands and are willing to pay higher prices whereas commercial processors buy large lots and pay significantly lower prices.

A major factor that I explore in detail in my analysis is the impact of the seller on the price of a given lot. As mentioned in the discussion of the data set, different boats use different types of gear, take trips of different length, and handle the caught fish differently. This may impact the prices they receive at auction because these variables affect freshness and quality of fish. In an attempt to analyze these effects I use two approaches: a boat fixed effects model, in which each boat is represented with a dummy variable, and a boat characteristics model, in which the length of the boat, the gear type, and the length of trip are included in the model. Since the boat characteristics are almost always constant throughout the six-year period for each vessel, the two approaches are mutually exclusive. Lee (2014) found that boats characterized as trawlers received higher prices for their fish, while boats that went out for longer trips received lower prices. To control for these effects I include dummy variables for the use of gillnets and for multiple day trips in the model; the coefficients for both variables are expected to be positive. I also include the length of the boat in the boat characteristics model. Although longer boats tend to be trawlers and go out for multi-day trips, they may be better able to store the fish on ice out of the sun, and thus length may have an independent, and positive, impact on the price of a lot.

Another determinant of price is the weight of the lot. As stated earlier, lots can range from 1 lb. to 1,200 lbs. One would expect the price per pound to decline as lots get larger for two reasons. First, there may be economies of scale in terms of handling larger lots of fish which may reduce the price per pound paid. Second, many of the buyers at PFEX do not purchase larger lots of fish because they sell their fish locally, and do not process the fish or sell it to more distant markets. The decrease in the number of bidders may reduce the demand for the larger lots, thus translating into a lower price per pound.

In addition to the weight of the individual lots, the total weight of fish landed at the exchange on a given day is also a determinant of price. Since fish are perishable almost all of the fish brought to the exchange is sold the day it is landed because it cannot be stored for a long period as inventory. On days in which a large overall quantity of fish is landed one would expect the price to fall in an effort to clear the market.

Although the majority of fish are sold on the day of landing, a small amount of fish are held over 1-3 days. To account for this, I use dummy variables to indicate that the fish were not landed the day of the auction. These lagged variables could lead to a depletion of price of fish. Finally, as discussed earlier, the cumulative landing variable is a possible reputation effect that could either inflate or deflate the prices.

Section V: Estimation Strategy and Results

Two different models are used to explain the variation in the prices paid for different lots of fish. The fixed effects (FE) model may be written as

$$\ln P_{ijkt} = \beta_1 LOT_{ijkt} + \beta_2 LOT_{ijkt}^2 + \theta TOTWEIGHT_t + F_i + V_j + B_k + D_t + M_t + Y_t + \varepsilon_{ijkt}$$

and the boat characteristics (BC) model be written as

$$\ln P_{ijkt} = \beta_1 LOT_{ijkt} + \beta_2 LOT_{ijkt}^2 + \theta_t TOTWEIGHT_t + F_i + B_k + \gamma_1 Gillnet_j + \gamma_2 MultipleDay + \gamma_3 Length + D_t + M_t + Y_t + \varepsilon_{ijkt}$$

where here P_{ijkt} is the price of the i th type of fish sold by the j th vessel to the k th buyer at time t , Lot_{ijkt} is the weight of the lot of the i th fish sold by vessel j to buyer k at time t , $TOTWEIGHT_t$ is the total weight of all of the fish landed on day t , the F_i , V_j , B_k , D_t , M_t , Y_t are fish, vessel, buyer, day, month, and year effects, and ε_{ijkt} is an idiosyncratic error term.

The FE model and the BC model may be estimated with OLS if all of the explanatory variables are exogenously determined. Previous research by Grady and Kennedy (2010) and Lee (2014) have suggested that the daily aggregate quantity, or $TOTWEIGHT$, may be simultaneously determined with price, and therefore, correlated with the error term, if sellers can hold inventory or otherwise adjust the timing of product delivery. Sellers at the PFEX may reject

a price for a given lot if they feel it is too low, and then hold the fish over for sale the next day. In addition, there is some evidence that sellers may adjust their landing date if they know that a large vessel will be landing in the near future. As a result, it is possible that the TOTWEIGHT variable is not exogenous.

In order to correct for this potential endogeneity I use an instrumental variables regression approach using weather factors as an instrument for the total weight variable. As stated in the data summary, the weather data comes from a weather buoy located in the Gulf of Maine, and thus should capture the effects of changes in weather on the total weight of fish sold at the exchange on a given day. The variables *atmos13*, *wav13*, and *wndgst13*, represent the average atmospheric pressure, average wave height, and average maximum wind gust for the three days prior to the day the fish were landed. The FE and BC models were thus estimated using two-stage least squares with *atmos13*, *wav13*, and *wndgst13* as instruments for *Totweight*.

The estimated coefficients for the three instruments from the first-stage equation for the FE and BC models are as follows (t-statistics are reported in parentheses):

Table 8: First-Stage Estimation Results

	FE Model	BC Model
<i>Atmos</i>	176.16*** (40.62)	193.78*** (43.07)
<i>Wav13</i>	-1970.19*** (239.11)	-1994.31*** (230.68)
<i>Wndgst13</i>	-432.06*** (61.16)	-417.51*** (61.81)
Adjusted R²	.49	.48

All other right-hand side variables were included in the first-stage equation.

All of the estimated coefficients are of the expected sign and are significant at the 1% level. In addition, the average adjusted R² is .485, implying a reasonably good fit for the first-stage model.

The Durbin/Hu-Hausman test was then employed to test the null hypothesis that *totweight* is exogenous. This hypothesis was rejected at the 1% level for both models, thus justifying the use of instrumental variables estimation. Next, in both models I tested for the presence of heteroskedasticity; the null hypothesis that the errors are homoskedastic may be rejected using the Pagan-Hall test at the 1% level. To correct for heteroskedasticity the models were estimated with robust standard errors that are clustered at the boat level.

The estimated coefficients for the FE and BC models, together with their robust standard errors clustered at the boat level, are presented in Appendix Table 1. As discussed in the data section, there are reasons to believe that the price of fish may vary by the day of the week or the month of the year. The PFEX is closed on Fridays and Saturdays, so fisherman who fish on Thursday through Saturday land their fish for sale on Sunday; as a result, the amount of fish landed on Sundays is approximately twice the amount landed on other days. Controlling for the total amount of fish landed on a given day, it would appear that the availability of fish on Sundays attracts more buyers, as fish prices are 14.1% higher relative to the omitted day Monday. In both models the average price is about 3.7% higher compared to Mondays, a result that is significant at the 1% level.

The price of fish may vary by month or year because seasonal fluctuations in weather or the restrictions imposed by quota limits. The estimated coefficients for the months of April and May are positive and significant at the 10% level or better, a result that is consistent with a reduction in supply as boats reach the end of their quota limits in May. The price of fish drops sharply in June, reflecting the renewal of quota limits and better fishing conditions. The price of fish increases in September and October, months that coincide with the beginning of stormy fall weather and hurricane season. Finally, the price of fish increases in December, reflecting the lower supply in this month and possible increases in demand resulting from the Holidays.

The estimated coefficients of the year dummy variables are all positive and significant at the 1% level, indicating an increase in the price of fish relative to the omitted year, 2009. The National Oceanic and Atmospheric Administration (NOAA) is responsible for maintaining the health of the groundfish stock in the Gulf of Maine. In 2010 NOAA switched from a “days at sea” form of regulation to a quota system of regulation, which greatly reduced the amount of fish that fishermen in the Gulf of Maine were allowed to land. As a result, the average price of fish

increased sharply between 2009 and 2010, and continued to climb in successive years as the quota.

The estimated coefficients for the item variables are all significantly different from zero at the 1% level, implying significant variations in the prices paid for different types and sizes of fish. The omitted item in this table is large Cod; the estimated coefficients for medium and small Cod are both negative and significant, implying that the price of Cod falls as the size of the fish decreases. This pattern is repeated throughout the table for all species of fish. This result is consistent with the fact that buyers are willing to pay a higher price for larger fish, as larger fish provide a higher yield than smaller fish. The results also indicate significant differences in the average prices paid by the different buyers in our sample. Major fish processors, like Channel Fish Processing Co., Great Eastern Seafood, and Tri-State Seafoods pay significantly less for their fish, while buyers that focus on sale to restaurants or local fish stores, like Legal Seafood and Browne Trading Co. pay higher prices. A relatively new buyer, Sea Salt, LLC, a Community Supported Agriculture organization, offers members the right to purchase a fixed amount of seafood each month, and offers the highest prices at the PFEX.

A major focus of this study is determining whether or not various boats obtain different prices for their catch, and if so, why. At this point I note that the estimated coefficients of many of the boat variables in the FE model are statistically different from 0 at the 1% level, indicating the possible existence of reputation effects that determine the price that each boat receives. I return to a discussion of this result later in this section.

Our next step was to conduct tests to see if day, month, year, item, seller and boat dummies are all zero. As the results in the following table indicate, each of these hypotheses may be rejected at the 1% level, so I retain each of these variables throughout the analysis.

Table 9

Hypothesis	Chi2-Stat	Chi2-Stat
	<i>Boat Fixed Effects</i>	<i>Boat Characteristics</i>
Day Effects = 0	36.17, 0.00	38.16, 0.00
Month Effects = 0	793.19, 0.00	602.77, 0.00
Year Effects = 0	751.30, 0.00	791.10, 0.00
Boat Effects = 0	2.5e^09, 0.00	59.17, 0.00
Buyer Effects = 0	18789.32, 0.00	38494.98, 0.00
Item Effects = 0	3.2e^06, 0.00	6.3e^06, 0.00

Turning next to the continuous variables, weight represents the weight of a given lot which may range from one pound to over 1,200 pounds. Many buyers in the sample purchase only smaller lots (< 300 pounds), as they do not purchase fish for processing, but rather for resale to local restaurants and fish stores. As the size of the lot increases the number of possible buyers decreases, thus decreasing demand and the price per pound, but presumably at a decreasing rate. This hypothesis is consistent with the negative coefficient for *weight* and the positive coefficient for *weight*², both of which are significant at the 1% level. The coefficient for *totweight*, the total amount of fish sold on a given day, is negative and significant at the 1% level, implying that the market price must decline to clear the market on days on which a large amount of fish is landed. Finally, the coefficient of *old*, a dummy variable for any lot that was landed prior to the auction date, is positive but insignificant, contradicting the hypothesis that older fish would receive a lower price. It should be noted that this coefficient was negative and significant in the OLS models, but became positive and significant in the IV equations.

Returning to the estimated coefficients of the boat dummy variables in the FE model, I note that the coefficients represent the price per pound of a given boat relative to the omitted boat, the American Heritage. In an effort to facilitate the rankings of the boats in terms of the price per pound they receive for their catch, the model was re-estimated, deleting the constant term and including a dummy variable for every boat in the sample – the results are presented in Table 10. The results indicate that the Harmony receives the highest price per pound for its fish with an estimated coefficient of 1.119, which is slightly above the estimated coefficient of 1.108

for the Teresa Marie 4 and the Teresa Marie III. It is of interest to note that the buyer Sea Salt, LLC, which, as mentioned earlier, is a Community Supported Agriculture organization and advertises that it purchases only the freshest and best fish, buys its fish from the Harmony.

I have argued that the estimated coefficients for the boat dummy variables may be interpreted as a “reputation effect” or the impact of the boat and captain on the price received for a given lot of fish, so long as I controlled for the day, month, and year in which the item was sold, the type and size of fish, the total weight of fish landed on a given day, and the firm that purchased the item. Tests of the null hypothesis that estimated the coefficients are zero, or that they are statistically equal to one another were all rejected at the 1% confidence level, showing that the reputation effects vary across boats. The estimated coefficients for the boat variables tell us which boats receive the highest price per pound, but not why they receive premium prices. In an effort to gain some insight into the why I estimate the boat characteristics (BC) model, which replaces the boat binary variables with three different characteristics of each boat that may influence the price they receive for their fish:

- 1) Gear Type: gillnet = 1 Trawl = 0
- 2) Length of Trip: Multipliedays = 1 Day trip = 0
- 3) Length of boat: measured in feet

The estimated coefficients for the BC model are presented in the second column of Appendix Table 1. The estimated coefficients for *weight*, *weight*², *totweight*, *old*, and the day, month, year, buyer, and item fixed effects are all quite stable across specifications. The estimated coefficient for boat length is positive and significant at the 1% level, indicating that larger boats receive higher prices for their fish than smaller boats, controlling for gear type and length of trip. One possible explanation for this result is that larger boats may be able to carry more ice and provide better storage for the fish in their holds than smaller boats that may have to store the fish on deck. The estimated coefficient for gillnet is positive and significant at the 1% level, indicating that boats that employ gillnets receive higher prices than boats that catch their fish using trawl nets. Trawlers drag conical shaped nets behind their boats to catch fish, with the fish winding up at the smaller end of the net. As the boat catches more fish, the fish already in the net become compressed, thus reducing their yield and value to buyers. Finally, the estimated

coefficient for multiple days is positive but insignificant, indicating the boats going out for multi-day trips are not penalized relative to day boats. One possible explanation for this finding is that boats that go out for longer trips tend to be larger, and as discussed above, may be able to maintain the freshness of their fish with more ice and better holds.

The estimated coefficients of the boat variables in the fixed effects model presumably capture the impact of the boat characteristics, gear type, trip length, and boat length, together with any unobservable factors such as the skill of the captain, the type of ice used to store the fish (shaved vs. cubes), where the fish are stored after the catch (hold vs. deck), how the fish are stored (randomly vs. head-to-tail), etc. If the observable boat characteristics are of primary importance, one would expect that longer boats that use gillnets to have larger coefficients in the FE models, and that a ranking of the estimated coefficients would be independent of trip length. On the other hand, if the unobservable factors were of primary importance in determining the estimated coefficients in the FE model, there may be no relationship between a ranking of the estimated coefficients and the observable boat characteristics. To explore this issue Table 10 presents the estimated coefficient for each boat in the FE model, together with its gear type, trip length, and boat length.

It is important to compare the results from our reputation effects analysis to the results shown in our regressions. Ideally, the results from this test would be consistent with the results from the regression analysis conducted above. I first conduct a simple t-test to test the hypothesis that the mean rankings of the day boats and multi-day boats are the same. The mean ranking for multiday boats is .948 compared to the mean ranking for day boats of .873. A t-test of the hypothesis that the two sample means are the same (the difference between them is 0) cannot be rejected at the 5% level. This confirms our result from the regression in showing that there is no difference between the coefficients of boats based on trip length.

Table 10

Vessel	Coefficient	Gear Type	Trip Length	Length
Harmony	1.119271	Trawl	MultiDay	85.3
Teresa Marie 4	1.108256	Trawl	MultiDay	81.2
Teresa Marie III	1.098801	Trawl	MultiDay	74
Marion J	1.039875	Gillnet	Day	37.3
North Star	0.9693263	Trawl	Day	42.4
Maria & Dorothy	0.9459052	Gillnet	MultiDay	44
Rachel T	0.9278566	Gillnet	MultiDay	43
Heidi & Elisabeth	0.9147982	Gillnet	Day	43
Shannon Kristine	0.9109257	Gillnet	MultiDay	46
American Heritage	0.9099599	Trawl	MultiDay	61.7
Sara Gale	0.9053017	Gillnet	Day	38.1
Pretender	0.9021504	Gillnet	Day	38
Pamela Grace	0.8995469	Gillnet	Day	39.6
Miss Maura	0.8980392	Gillnet	Day	42
Hannah Jo	0.8953445	Gillnet	Day	38
Safe Haven	0.8870855	Gillnet	Day	42
Leslie & Jessica	0.8863366	Trawl	MultiDay	57.3
High Roller	0.880497	Trawl	Day	40
Theresa Irene	0.8794779	Gillnet	Day	42
Rolling Stone	0.8774186	Gillnet	Day	45
Gulf Venture	0.8753682	Gillnet	MultiDay	39.9
Bridget Leigh	0.8728697	Gillnet	Day	43
Jeanne C	0.8713107	Trawl	Day	35.8
Lauren Dorothy 2	0.8630735	Trawl	MultiDay	53
Free Bird	0.8493503	Trawl	Day	37.7
Lady Mae	0.8124279	Gillnet	Day	36
Black Beauty	0.7864137	Trawl	MultiDay	63.2
Sweet Misery	0.4998015	Gillnet	Day	42

Next I analyze the null hypothesis that the mean rankings are the same for trawlers and gillnetters. I find that trawlers have an average ranking of 0.940 whereas gillnetters have an average ranking of 0.879. This difference is not significant at the 10% level. My regression results showed that gillnetters command a higher price than trawlers but this test indicates that there is no difference in the average price commanded by the two. I believe the difference is caused because the estimated coefficients from the boat characteristics model controls for the effect of boat length and trip length – the coefficients in the table above were obtained from the fixed effects model which does not control for any of these factors.

The final result I compare is the relationship between vessel rankings and boat length. Our regression output showed us that bigger boats get a higher price for their fish. To test this result I need to use a different method because the boat length data is a continuous variable, not a discrete variables like the others. I use a pair-wise correlation matrix in an attempt to compute the correlation between the rankings and boat length. The result is show below. The correlation between the rankings and boat length is positive and significant at the 1% level, which is consistent with the regression results I solved for earlier.

	Coefficient	LENGTH
Coefficient	1.0000	
LENGTH	0.5091 0.0057	1.0000

The results of this analysis are thus mixed. In the BC model boats that employ gillnets receive higher prices for their fish, but trip length has no impact of prices. When I look at the boat rankings from the fixed effect model, the rankings are independent of gear type and trip length. In both models, however, larger boats receive higher prices than smaller prices. It thus appears that the types of unobservable characteristics discussed above, the skill of the captain and crew, method used to store the fish, etc., may play a very important role in determining the prices that each boat receives for its fish.

Another aspect of the reputation effect that I want to study is whether or not the effects are stable over time. To test this I look to see if the estimated boat coefficients, which are a proxy for reputation effect, are constant over time. One way of examining this would be to add interaction terms between the boat dummies and the year dummies to the model. Unfortunately, there are 28 boats and $6-1 = 5$ year dummies, so this potentially could be adding 140 variables to the model. Adding this many variables may create a large amount of multicollinearity that would adversely affect the estimated standard errors. In addition, I am really looking to see not whether the estimated coefficients are the same over time, but rather whether or not the rankings of the boats are stable over time. The real question, for example, is whether or not the Harmony is the highest ranked boat each year, not whether its estimated coefficient is stable over time.

Alternatively, I could estimate the FE equation 6 times, once for each year, and then test if rankings are constant over time.

To test for the stability of the reputation effect over time the FE model was estimated each year with two adjustments: (i) the year fixed effects were dropped, since the model was estimated using the data from a single year, and (ii) some of the boat dummy variables were deleted each year since most boats did not land fish at the PFEX each year during 2009-14. The results from running this estimation are shown in the table below. I cannot simply just observe the rankings and prove that one always looks to be the highest or the smallest. In order to test if the rankings are stable over time I had to remove the observations that had missing coefficients for certain years. The final sample was 10 boats that had been present at the exchange for all 6 years of our sample. The coefficients for each of these units can be seen in Table 11 shown below and see Appendix Table 2 for a full list of the 28 boats with coefficients. I used Friedman's nonparametric two-way analysis of variance and Kendall's coefficient of concordance to test the null hypothesis that the rankings are not stable over time. Kendall's coefficient of concordance is distributed as a chi-squared and is bounded between 0 and 1, with a higher value meaning the rankings are correlated over time. In this case Kendall's coefficient of concordance is equal to 0.9509, which is significant at the 1% level. Thus, for the 10 boats for which I have complete data, I reject the null hypothesis that the annual rankings are random over time, and conclude that there is some evidence that the higher ranked boats in one year remain among the higher ranked boats in later years.

Table 11

Vessel	Heidi & Elisabeth	High Roller	Jeanne C	Maria & Dorothy	Pamela Grace	Rachel T	Rolling Stone	Safe Haven	Shannon Kristine	Teresa Marie III
2009	0.0666	-0.0566	0.0045	0.0180	-0.0110	0.0266	-0.0533	-0.0072	0.0359	0.3893
2010	0.7905	0.8097	0.6779	0.8616	0.7264	0.8737	0.7833	0.8056	0.8153	1.0800
2011	1.1107	1.1285	1.0819	1.1449	1.1175	1.1339	1.0758	1.0765	1.1068	1.0596
2012	1.3466	1.2046	1.3278	1.3747	1.3285	1.3276	1.3307	1.3342	1.3217	1.2447
2013	1.4635	1.3068	1.3646	1.5063	1.4839	1.4680	1.4622	1.4596	1.4259	1.6403
2014	1.3920	1.0916	1.2869	1.3905	1.3537	1.3894	1.3595	1.3415	1.3464	1.3699

The results thus far indicate that the boats in our sample receive different prices for the fish that they land, but that not all of the variation in the prices is due to the type of gear they employ, the length of the trips they take, and the size of their boats. For example, the estimates from the BC model indicate that boats that use gillnets receive higher prices for their fish, but the three highest ranked boats from the FE model, Harmony, Teresa Marie 4 and Teresa Marie III all employ trawl nets. It would thus appear that other non-observable factors, such as the skill of the captain and the crew and the manner in which the fish are handled play an important role in determining the price received by a given boat. The importance of these non-observable factors is consistent with the fact that the boats with the second and third highest rankings, the Teresa Marie 4 and the Teresa Marie III, have the same owner¹ and thus share many of these non-observable factors.

My final piece of analysis is conducted around the cumulative landing variable mentioned earlier. When a boat lands at the PFEX for the first time the buyers will have little if any knowledge about the captain or the methods used in handling the fish. Over time, however, as the boat makes successive landings buyers will have more opportunities to learn about the quality of the fish, which in turn will help to establish the boat or captain's reputation. It would thus be useful to examine the relationship between the number of times buyers and sellers interact, and the prices the sellers receive for their catch. To explore this relationship I calculated the running total of the number of times each boat landed fish at the PFEX, or *cumlanding*, during the period 2009-14. The data start on March 10, 2009 so any boat landing fish then will have a value of *cumlanding* = 1, regardless if they have landed hundreds of times at the PFEX prior to this date. In an effort to minimize this issue, *cumlanding* is computed beginning March 10, 2009, but only data during 2010 to 2014 are used to explore the relationship between the prices and *cumlanding*. Boats that land regularly at the PFEX may have values of *cumlanding* in excess of 100 in 2014, while boats that didn't land any fish in 2009 will have a value of *cumlanding* = 1 when they first land fish in 2010.

To determine how long it takes to establish a "reputation" at the PFEX ten different dummy variables were created, with *firstlanding* = 1 if *cumlanding* = 1 and 0 otherwise, *secondlanding* = 1 if *cumlanding* = 2, and 0 otherwise, up to *tenthlanding* = 1 if *cumlanding* =

¹ The Teresa Marie 4 is not the successor of the Teresa Marie III; both boats landed fish throughout the period 2009 – 2014, and thus are two different boats with the same owner.

10, and 0 otherwise. The BC model was then estimated, first including *firstlanding*, then re-estimated adding *secondlanding*, etc. through the *tenthlanding* to test whether boats that land fish for the first time at the PFEX are penalized in terms of receiving lower prices, and if so, for how long the penalty lasts. The results from this estimation are shown in column 1 of Appendix Table 3. The estimated coefficient of *firstlanding* was negative and significant at the 1% level in every case but one, and in almost every case the estimated coefficients for the additional landings were statistically insignificant. In general, boats landing fish for the first time at the PFEX receive prices per pound approximately 10.0 - 12.5% lower than the prices they receive for later landings, but this penalty disappears after the first landing.

Next, the model was estimated with the *firstlanding* variable and the continuous variable *cumlanding* to determine if fishermen receive higher prices as they increased their landings at the PFEX after the first landing. The estimated coefficient on *firstlanding* is -.10.81 and is significant at the 1% level, indicating that boats landing for the first time suffer a 10.81% penalty in price per pound. The estimated coefficient for *cumlanding* is positive and marginally significant at the 13% level, providing weak support for the hypothesis that sellers receive higher prices as the land more frequently at the PFEX. This can be seen in column 2 of Appendix Table 2.

To test whether the relationship between the log of price and *cumlanding* is linear I ranked the values of *cumlanding* from lowest to highest, and then divided the observations into quintiles. I then created four different dummy variables, *cumlanding20* = 1 if *cumlanding* is in the bottom quintile all landings (≤ 39), *cumlanding40* = 1 if *cumlanding* is in the second quintile ($39 < \text{cumlanding} < 60$), *cumlanding60* if *cumlanding* is in the third quintile ($60 \leq \text{cumlanding} < 90$), and *cumlanding80* if *cumlanding* is in the fourth quintile ($90 \leq \text{cumlanding} < 126$); the top quintile, with values of *cumlanding* > 126 was the omitted variable.

The estimated coefficients for this model are in the third column of appendix table 3. The estimated coefficient for *firstlanding* is -.1249 and is significant at the 1% level, a result that is consistent with the estimates of the other models. The estimated coefficients for the quintile dummy variables are all negative and significant at the 10% level or better, with the exception of *cumlanding1020*, which is statistically insignificant. The negative coefficients for the quintile dummy variables indicate that lots sold from boats with values of *cumlandings* in the bottom

80% sell at a discount relative to lots sold by boats with more than 126 cumulative landings. In an effort to explore this issue further I tested the following two null hypotheses:

$$H_0: \text{cumlanding20} = \text{cumlanding40} = \text{cumlanding60} = \text{cumlanding80} = 0$$

$$H_0: \text{cumlanding20} = \text{cumlanding40} = \text{cumlanding60} = \text{cumlanding80}$$

The first hypothesis was rejected at the 1% confidence level, indicating that the prices for the bottom four quintiles were significantly different than prices for the top quintile; i.e. lots sold from boats with more than 126 cumulative landings received higher prices. I was unable to reject the second hypothesis at the 10% level, however, indicating that the relative price discount for the lower four quintiles is the same.

It is important to note that my findings do not tell me anything about the direction of the relationship between price and *cumlandings*. It may be the case that some boats receive relatively higher prices when they first land fish at the PFEX, and as a result they continue to land fish there; in this case a higher price may be said to cause an increase in *cumlandings* over time. Alternatively, some boats may receive lower prices when they first land fish at the PFEX, but over time they learn to improve the quality of their catch, and thus receive higher prices over time; in this case an increase in *cumlandings* leads to higher prices over time.

Section VI: Conclusions

The results from this analysis show mixed effects on the pricing of fish at the Portland Fish Exchange. As stated earlier, I see significant effects on price based on the day, month and year the fish are sold. Additionally, I find that certain buyers may inflate the price of fish due to outside demand structures. Similar to previous research (McConnell and Strand, Lee) I find that type of gear and boat length do play a significant role in the determinants of price. But the results of my two specifications are mixed. The BC model shows that the use of gillnets receive higher prices for their fish but trip length has no impact on price but the FE model shows that boat coefficient rankings are independent of gear type and trip length. This shows that there are unobservable characteristics that may play an important role in determining the prices that each boat receives.

This theory is supported by factual evidence. The boats with the three highest rankings all employ trawl nets, which contradicts the BC model indication that boats that use gillnets

command a higher price for their fish. The potential importance of non-observable factors is also supported by the fact that the boats with the second and third highest rankings have the same owner and thus potentially share many of these non-observable characteristics.

I also find that annual rankings over time are consistent, in that I find some evidence that higher ranked boats in one year remain among the higher ranked boats in later years. This shows that reputation effects are stable over time and could potentially lead to certain boats getting consistently higher prices at the auction. Additionally, I found boats receive a penalty for their first cumulative landing at the exchange but this penalty completely disappears after the first landing. I also find that lots sold from boats with values of cumulative landing in the bottom 80% sell at a discount relative to lots sold by boats with more than 126 cumulative landings but was unable to confirm that there was any difference in discount among the 4 lower quintiles. As noted earlier, my findings do not tell me anything about the direction of the relationship between price and *cumlanding*.

Going forward, it would be beneficial to the literature to attempt to analyze or control for the unobservable effects, like crew and captain, which potentially cause my results to be mixed. This could potentially clarify and show a more concrete effect of the various boat characteristics. Additionally, the study of cumulative landings and reputation over time provide a new platform to continue to study relationship management between buyers and sellers at these auctions. Given that boats know premiums for good quality fish are consistent over time, in these particular auctions, boats may be incentivized to improve and maintain the quality of their catch in order to command a higher price. These reputation effects could be broadened to larger scale, international auctions as well, where larger boat size and stricter regulations could possibly add more control variables.

References:

- McConnell, K., and I. Strand. 2000. "Hedonic Prices for Fish: Tuna Prices in Hawaii." *American Journal of Agricultural Economics* 82:133–44.
- Kristofersson, D., and K. Rickertsen. 2004. "Efficient Estimation of Hedonic Inverse Input Demand Systems." *American Journal of Agricultural Economics* 86:1127–37.
- Graddy, K., and P. Kennedy. 2010. "When are Supply and Demand Determined Recursively Rather than Simultaneously?" *Eastern Economic Journal* 36:188–97.
- Larkin, S., and G. Sylvia. 1999. "Firm-level Hedonic Analysis of US Produced Surimi: Implications for Processors and Resource Managers." *Marine Resource Economics* 14:179–98.
- Roheim, C., L. Gardiner, and F. Asche. 2007. "Value of Brands and Other Attributes: Hedonic Analysis of Retail Frozen Fish in the UK." *Marine Resource Economics* 22:239–53.
- Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy* 82:34–55.

Appendix Tables

Appendix Table 1:

VARIABLES	(1) lnprice	(2) lnprice
totweight	-5.45e-06*** (1.30e-06)	-5.42e-06*** (1.29e-06)
weight	-0.000373*** (4.60e-05)	-0.000360*** (4.33e-05)
weight2	1.60e-07*** (3.43e-08)	1.54e-07*** (3.29e-08)
old	0.0269 (0.0281)	0.0269 (0.0279)
Sunday	0.141*** (0.0265)	0.141*** (0.0264)
Thursday	0.0105 (0.00961)	0.0111 (0.00945)
Tuesday	-0.0216* (0.0120)	-0.0231* (0.0121)
Wednesday	0.0371*** (0.0100)	0.0373*** (0.00957)
February	-0.00775 (0.0578)	-0.00619 (0.0576)
March	-0.0151 (0.0359)	-0.00716 (0.0393)
April	0.139*** (0.0330)	0.131*** (0.0352)
May	0.0516* (0.0309)	0.0411 (0.0317)
June	-0.0789** (0.0313)	-0.0877*** (0.0335)
July	0.0148 (0.0352)	0.00672 (0.0376)
August	0.00722 (0.0308)	-0.00639 (0.0329)
September	0.0752** (0.0323)	0.0623* (0.0348)
October	0.0872*** (0.0276)	0.0794*** (0.0299)
November	-0.0245 (0.0319)	-0.0313 (0.0336)
December	0.0661* (0.0389)	0.0642* (0.0378)
2010	0.158*** (0.0410)	0.158*** (0.0392)
2011	0.233*** (0.0321)	0.237*** (0.0319)
2012	0.337*** (0.0216)	0.337*** (0.0211)
2013	0.337*** (0.0296)	0.338*** (0.0296)
2014	0.396*** (0.0259)	0.394*** (0.0261)
length		0.00467*** (0.000716)
gillnet		0.0269** (0.0117)
multipliedays		0.00341 (0.0119)
Constant	0.910*** (0.0557)	0.687*** (0.0537)
Fixed Effects		
Item	Y	Y
Seller/Boat	Y	
Buyer	Y	Y
Observations	70,646	70,646
R-Squared	0.724	0.723

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2:

Vessel	2009	2010	2011	2012	2013	2014
American Heritage	0	0	0	0	0	0.0852
Black Beauty	0	0	1.1322	0	0	0
Bridget Leigh	0	0	0	0	1.3409	1.3874
Free Bird	-0.0348	0.6562	1.0615	1.2978	1.4345	0
Gulf Venture	0	0	0	0	1.4363	1.3520
Hannah Jo	-0.0233	0.8081	1.0833	1.3385	0	1.3241
Harmony	0.1909	0.9409	0.9741	1.6219	1.6220	0
Heidi & Elisabeth	0.0666	0.7905	1.1107	1.3466	1.4635	1.3920
High Roller	-0.0566	0.8097	1.1285	1.2046	1.3068	1.0916
Jeanne C	0.0045	0.6779	1.0819	1.3278	1.3646	1.2869
Lady Mae	0	0.7256	0	0	0	0
Lauren Dorothy 2	-0.1247	0.6967	1.0958	1.2292	0	0
Leslie & Jessica	-0.1074	0.8306	1.0985	1.3269	1.3438	0
Maria & Dorothy	0.0180	0.8616	1.1449	1.3747	1.5063	1.390
Marion J	0	0	0	0	0	1.555
Miss Maura	0	0	0	0	0	1.322
North Star	0	0.9035	1.1341	1.2640	0	0
Pamela Grace	-0.0110	0.7264	1.1175	1.3285	1.4839	1.3537
Pretender	-0.0064	0.8213	1.1163	1.3196	0	0
Rachel T	0.0266	0.8737	1.1339	1.3276	1.4680	1.3894
Rolling Stone	-0.0533	0.7833	1.0758	1.3307	1.4622	1.3595
Safe Haven	-0.0072	0.8056	1.0765	1.3342	1.4596	1.3415
Sara Gale	-0.0502	0.8333	1.1031	1.3431	1.4172	0
Shannon Kristine	0.0359	0.8153	1.1068	1.3217	1.4259	1.3464
Sweet Misery	0	0	0	0	1.1421	0
Teresa Marie 4	0.2193	1.1307	1.1503	1.5165	1.4970	0
Teresa Marie III	0.3893	1.0800	1.0596	1.2447	1.6403	1.3699
Theresa Irene	0	0.8129	1.1016	1.3231	1.4480	1.3311

Appendix Table 3:

VARIABLES	(1) lnprice	(2) lnprice	(3) lnprice
totweight	-5.89e-06*** (1.82e-06)	-5.94e-06*** (1.82e-06)	-6.10e-06*** (1.85e-06)
weight	-0.000327*** (3.89e-05)	-0.000334*** (4.03e-05)	-0.000330*** (4.21e-05)
weight2	1.23e-07*** (3.30e-08)	1.25e-07*** (3.37e-08)	1.24e-07*** (3.48e-08)
old	0.00448 (0.0283)	0.00904 (0.0280)	0.00738 (0.0277)
firstlanding	-0.118*** (0.0395)	-0.108*** (0.0380)	-0.125*** (0.0400)
secondlanding	-0.0371 (0.0642)		
thirdlanding	-0.0785 (0.0753)		
fourthlanding	0.0247 (0.0824)		
fifthlanding	-0.00769 (0.0659)		
sixthlanding	-0.103 (0.108)		
seventhlanding	0.0803 (0.0839)		
eighthlanding	0.0392 (0.146)		
ninthlanding	0.131** (0.0547)		
tenthlanding	0.0343 (0.0630)		
gillnet	0.0232 (0.0144)	0.0162 (0.0175)	0.0239* (0.0129)
multipliedays	0.00925 (0.0149)	0.0143 (0.0162)	0.0156 (0.0159)
length	0.00401*** (0.000874)	0.00434*** (0.000686)	0.00401*** (0.000652)
cumlanding		0.000167 (0.000110)	
pct1020			-0.0146 (0.0197)
pct3040			-0.0321* (0.0167)
pct5060			-0.0493*** (0.0149)
pct7080			-0.0353*** (0.0129)
Constant	0.910*** (0.0580)	0.895*** (0.0536)	0.936*** (0.0542)
Fixed Effects			
Item	Y	Y	Y
Month	Y	Y	Y
Day	Y	Y	Y
Year	Y	Y	Y
Buyer	Y	Y	Y
Observations	56,310	56,310	56,310
R-squared	0.712	0.711	0.711

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1