PRICE-QUANTITY DYNAMICS, PREQUENTIAL ANALYSIS, AND YIELD

INSURANCE PREMIUM ESTIMATION OF DUNGENESS CRAB

A Dissertation

by

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ABSTRACT

This dissertation analyzes the Dungeness crab prices and quantities, which is conducted within three essays. The first essay studies the relationships among the West Coast Dungeness crab landing prices and quantities using cointegration analysis and directed acyclic graphs. The forecast tests are added to determine the number of cointegrating rank. Directed acyclic graphs are estimated using different algorithms for comparison and are used to discover the causality of the crab markets. The four states' crab prices are strongly connected contemporaneously. The price-quantity relationships exist among the California, Oregon and Washington markets because of their tri-state Dungeness crab project. The Alaska quantity does not affect and is not affected by the other prices and quantities possibly due to stock collapse in some areas of Alaska.

The second essay uses the three models to explore the prequential relationships among the West Coast states' Dungeness crab fisheries. A random walk and the 1-lag VAR outperform the 2-lag VAR. Most series in the random walk and the l-lag VAR are well-calibrated. For the Dungeness crab quantities, the random walk does slightly better than the 1-lag VAR; the 1-lag VAR dominates the random walk for the crab prices. The results are consistent with the literature on the Dungeness crab movement patterns. Information about the crab fishery management decision making are provided in this essay.

The third essay estimates the Dungeness crab yield insurance premiums and the probabilities of the indemnities being paid to the crab fishermen in each western coastal state using cointegration analysis, goodness-of-fit tests, and Monte Carlo simulation. The

lognormal distribution provides the best-fit for the Alaska crab yield and the logistic for the Oregon, Washington, and California yields, respectively. The log-logistic is found to be the best-fit for each state's prices. At 50%, 60%, 70%, and 80% yield coverage levels, Alaska has the highest insurance premiums and the highest probability of paying the indemnities, followed by California, and then Washington or Oregon.

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CHAPTER I

INTRODUCTION

Dungeness crab is among the top three most valuable crabs on the West Coast. During the period from 2003 to 2012, the Dungeness crab production ranged from 50 to 89 million pounds, which in the West Coast's total commercial crab production ranged from 33% to 62%. The crab fishery has an average annual value of approximately $140 million during the same period with more than 43% of the total crab fishery landing values on the West Coast.

Much literature on the Dungeness crab focused on its biology and ecology (e.g., Wild and Tasto 1983; Botsford et al. 1998; Stone and O'Clair 2001; Rasmuson 2013). However, the analyses of the crab prices and production are also important and provide some valuable information for the crab industry. Using economic and statistical models, this dissertation explores price-quantity relationships among the West Coast's Dungeness crab landing markets and considers an application of prequential analysis to the Dungeness crab prices and quantities. Also, the chance of the Dungeness crab yield losses faced by the fishermen and the crab-yield insurance premiums are estimated. The above topics are included in three main essays (Chapter II-IV), and each essay is stated as following:

The first essay, Chapter II, uses cointegration analysis and directed acyclic graphs to examine the price-quantity dynamics of the western coastal states' Dungeness crab landing markets including Alaska, Washington, Oregon, and California. Since the Dungeness crab market is special due to its perishable meat and its fishing regulation, the issue of the price-quantity causalities is particularly important in the four landing state markets. If price-quantity relationships exist among the four landing markets, each market is not viewed as a closed economy but an open economy. The directed acyclic graphs contain vertices, edges, and arrowheads to provide an illustration of causal relationships among the four states' Dungeness crab prices and quantities.

The second essay, Chapter II, conducts prequential analysis to compare the three models (a random walk model and two vector autoregression models) of the four western coastal states' Dungeness crab landing prices and quantities. As decisions concerning the crab prices and quantities are inherently uncertain and as many if not most decision analyses require expected utility or the entire probability distribution, the prequential analysis is mainly interesting. Pearson's chi-square test, Kolmogorov-Smirnov test and causal directed acyclic graphs are used to compare the accuracy of the three methods. The model Comparisons not only provide useful information on the Dungeness crab biology and ecology but also has beneficial implications for the Dungeness crab fishery management.

In the third essay (Chapter IV), each state's fishermen are exposed to the risks of large fluctuations and sharp declines in the Dungeness crab yield but do not have the option to buy a crab-yield insurance policy. Like crop-yield insurance, the crab-yield insurance per pound in cents may be used as a risk management tool to protect the fishermen against the yield and revenue losses. Vector error correction model and goodness-of-fit tests are used to find the parametric probability distributions best describing each western costal state's crab prices and yields. The probability distributions of the crab yields, those of the crab prices, and Monte Carlo simulation are employed to estimate the insurance premiums of the Dungeness crab yield insurance and the probabilities of the indemnities being paid to the crab fishermen at the coverage levels of 50%, 60%, 70%, and 80%.

CHAPTER II

PRICE-QUANTITY DYNAMICS IN THE DUNGENESS CRAB LANDING MARKETS

II.1 Introduction

Dungeness crab is an important commercial crab fishery along the West (Pacific) Coast of the United States (US). During the period from 2003 to 2012, the West Coast's total commercial crab landing production ranged from 119 to 165 million pounds. The production of Dungeness crab ranged from 50 to 89 million pounds. The commercial Dungeness crab fishery has an average annual value of approximately $140 million during the same period with over 43% of the West Coast's total crab fishery landing revenues. These statistics show that the Dungeness crab is a high-value product among the West Coast's crab production[1].

To maintain stock productivity, the commercial Dungeness crab fishery is regulated by the Alaska, Washington, Oregon, and California state legislatures using the "3-S principle" which is based on the crab's sex, season, and size restrictions. Much literature such as Wild and Tasto (1983), Botsford et al. (1998), Stone and O'Clair (2001), and Rasmuson (2013) was concerned with the Dungeness crab biology and ecology. These studies emphasize that Dungeness crab plays a very important role in the West Coast. The analysis of the crab price and quantity is also important and has some beneficial implications for the crab industry. Most of the price-quantity studies 'described' the

[1] The statistical data were from the National Oceanic and Atmospheric Administration (NOAA)

phenomena of some specific regions/states (e.g., Demory 1990; Didier 2002;Dewees et al. 2004; Helliwell 2009). To our knowledge, no empirical research has 'examined' the Dungeness crab price and quantity relationships among the four western coastal state landing markets including Alaska, Washington, Oregon, and California.

Economic theory and intuition suggest that a relationship between price and quantity should exist. In practice, the relationships are examined via static models or dynamic causal models. The static methods, a time-invariant system, include the estimation of demand and/or supply functions in equilibrium but have commonly encountered two issues. First, researchers must assume either a quantity-dependent function (i.e., an ordinary function) or a price-dependent function (i.e., an inverse function). Second, the results of estimating the functions may violate the assumptions of economics. That is, the slopes of statistical curves may not equate these to Marshall's ceteris paribus curves (Moore 1914). With observational data, the existence of omitted variables results in the failure to explain the shifts in demands and supplies whose regularities sometimes look like demand, sometimes like supply, and sometimes neither (Working 1927). The dynamic causal models such as Directed Acyclic Graphs (DAGs) do not have the two problems discussed above but enable us to account for the time dependent effects (i.e. one variable moves the other variables). Mjelde and Bessler (2009) stated that the static models did not present how the relationships respond in the dynamic causal models. In other words, the dynamic but not the static models allow us to examine directly whether the price affects the quantity or is affected by the quantity. The causalities of prices and quantities for some commodities have been described in some studies (e.g., Marshall's (1920) fish market[2], Wang and Bessler's (2006) meat market[3], Helliwell's (2009) California Dungeness crab market[4]).

We employ DAGs and vector error correction models (VECM) to identify the causal contemporaneous relationships among the prices and the quantities in the four state Dungeness crab landing markets--Alaska, Washington, Oregon, and California. The principal objectives of the paper are twofold: (i) to understand the degree of the interconnectivity among the four crab landing markets and (ii) to assess whether the quantity-dependent function or the price-dependent function or both or neither exists in the four landing markets. First, the Dungeness crab market is special due to its perishable meat and its fishing regulation. This implies that the issue of the price-quantity causalities is particularly important in the four Dungeness crab landing markets. The important difference between previous studies and our study is that our study tests and examines the price-quantity causalities among the whole landing markets instead of the description of the trade between some specific regions used by some previous studies such as Demory (1990)[5] . If the causalities of the prices and quantities exist among the four landing markets, each state landing market would not be viewed as a closed economy but an open economy. The price-quantity interactions in the four state markets

[2] Marshall (1920) stated that the quantities caused changes in the prices in a fish market if the stock of fish was taken for granted.

[3] Wang and Bessler (2006) showed that retail prices controlled the quantities consumed for poultry and beef products and the quantity of pork controls the pork price.

[4] Helliwell (2009) reported that because most of the market crabs were caught within the first two weeks of the fishing season, there was a glut and lower prices.

[5] Demory (1990) stated that the California moved the Oregon and Washington price because approximate 70% of Oregon crab was marketed in California. However, Alaska market was excluded in this report.

should be considered by each States private and public sectors to make more accurate and complex decisions regarding fishing planning and management. Second, if our results show that price (quantity) is predetermined, the quantity (price)-dependent functions can feature the fundamental market structure; while if the price and the quantity contemporaneously cause each other, the problem of simultaneity would occur and have to be dealt with explicitly (Wang and Bessler 2006).

For the method application and improvement, our contributions include (i) We introduce the new test which combines the concept of Bessler and Wang's (2012) conjecture model and Kling and Bessler's (1985) forecast procedures to determine the number of cointegration vectors. The difference between the traditional tests[6] and the new tests is that the new tests choose the number of cointegrating rank based the comparison of the forecast performance of the VECM with different cointegration ranks. The VECM model using both the new and the traditional tests will be better suited to estimate and explain the real word than the model just using the traditional tests which do not consider the forecast evaluation. (ii) We compare and apply three DAGs models including greedy equivalence search (GES), Peter and Clark (PC) algorithm, and PC linear non-Gaussian acyclic model (PC-LiNGAM) in the Dungeness crab price-quantity analysis.

The remainder of the paper is organized as follows. A brief discussion of the commercial Dungeness crab industry and its landing data is in the next section, and this

[6] There are three test statistics: trace test, Schwarz Loss (SL), and Hannan and Quinn loss (HQ).

is followed by a discussion of the empirical methods. The empirical results are then offered. A summary concludes the paper.

II.2 Industry Overview and Data

The West Coast's Dungeness crab fishery began commercial fishing since at least 1917 (Miller 1976). The crab dwells in the Pacific Coast from the Pribilof Islands in Alaska to Magdalena Bay in Mexico (Stone and O'Clair 2001), but is not abundant south of Point Conception in California (Pauley et al. 1989). This implies that the commercial harvests of the Dungeness crab come from the four states including Alaska, Washington, Oregon, and California. In addition to meeting the licensing and permitting requirements, the four states' crab fishermen have to follow the 3-S principle with the "sex-size-season" regulatory system. The 3-S principle asserts that only sexually mature male crabs over the legal size limit are commercially harvested in the fishing seasons every year. The basic commercial crab-fishing regulations have been constant through time but the commercial fishing seasons vary by the management regions. California's commercial fishing season for Dungeness crab begins the middle of November or the beginning of December and continues through the end of June or the middle of July, and Oregon and Washington have similar fishing-season durations (Hackett et al. 2003). The Dungeness crab has different crabbing seasons throughout the Alaska waters. For example, in southeast Alaska, the season is open in all regions in October and November, open in most areas between the middle of June and of the middle of August, and open in designated regions during the periods from December through the end of

February. The season in Kodiak and Alaska Peninsula is open between May and the end of December[7]. The above information shows that the periods of opening and closing the crab fisheries in Alaska are obviously different from the periods in Washington, Oregon, and California. Moreover, the Dungeness crab stocks have collapsed in some regions of Alaska, possibly due to overfishing, sea otter predation, and adverse climatic changes (Woodby et al. 2005).

Every year the Dungeness crab fishing is banned in the several months when the female crabs are molting and mating or when the male crabs are molting. The extremely low catch in the prohibited months should be found easily in the Dungeness crab's monthly landing data and might be viewed as a nuisance in statistical analyses. In fact, the complete monthly landing data for the Dungeness crab to date are not available and the missing data problem may cause substantial biases in analyses. To avoid this problem, this study uses the annual landing data.

The data set we analyze consists of 53 annual state-level observations related to the West Coast's Dungeness crab landing market from 1950 to 2002. It includes the following variables: the commercial quantities of the crab landing in Alaska, Washington, Oregon and California in pounds of round (live) weight (lbs) and their landing prices (US cent/lb). The history series of the four state's quantities and prices are

[7] More information is available at
http://www.adfg.alaska.gov/static/fishing/pdfs/commercial/fishingseasons_cf.pdf.
Cited 30 November, 2013.

obtained from the NOAA's National Marine Fisheries Service (NOAA Fisheries). Data was also collected from 2003 through 2012 for an out-of-sample forecast evaluation.

The original data are transformed to the natural logarithm of the values of the variables to improve the normality of variables, and plots of the natural logarithm of each price and quantity series between 1950 and 2012 are given in figure II.1. Notice that for each market, landing price series appear to have trends over time and to be mean non-stationary processes. For the four landing quantity series, whether their processes are non-stationary is less obvious. Each states commercial Dungeness crab fishery has exhibited periods of high and low landings. Especially, between northern California and Washington, the crab fishery synchronously undergoes cyclic catch fluctuations in abundance (Botsford et al. 1998). The cycles are caused by: (i) predator-prey systems with both salmon and human as predictors, (ii) exogenous environmental forces such as ocean temperature, surface winds, alongshore flow, and sea level, (iii) density-dependent (biological) mechanisms containing density-dependent fecundity**,** an egg-predator worm and cannibalism (Botsford et al. 1998).

Summary statistics of the natural logarithms of the within-sample data from 1950 through 2002 are presented in table II.1. During the period, Washington had highest average Dungeness crab landings, followed by Oregon, California and Alaska. California's crab quantities appear to be most volatile among the four states' landings, as measured by Coefficient of variation representing the degree of dispersion in each series. For the four states' crab prices, California had the highest average, followed by Oregon, Washington and Alaska. It is noteworthy that California's crab had the highest average price but the lowest volatility in its prices. However, the crab prices in Alaska were the lowest in average but fluctuated most dramatically.

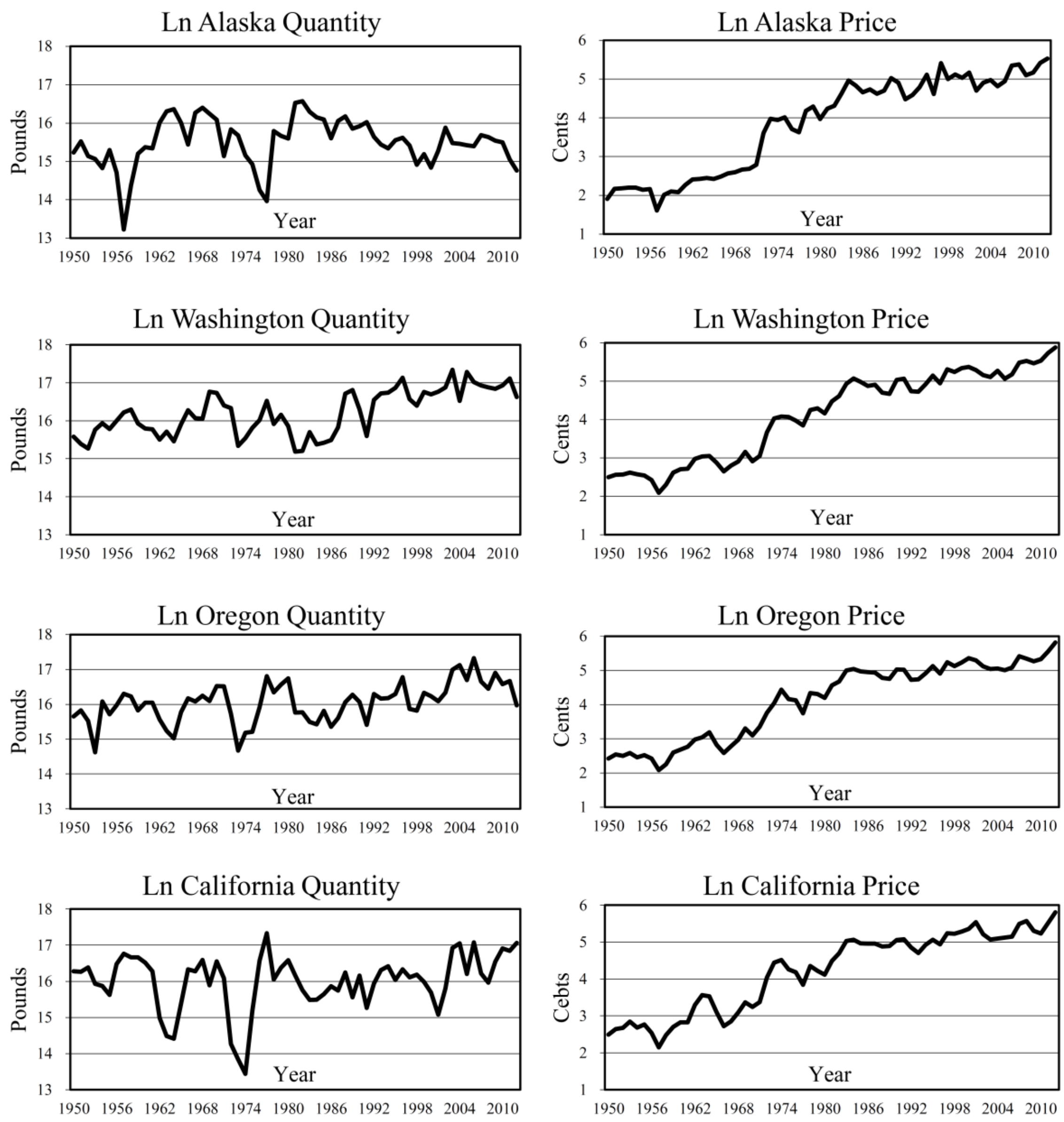

Figure II.1. Time Series Plots of Natural Logarithms of Dungeness Crab Quantities and Prices, 1950-2012

Table II.1. Summary Statistics on Natural Logarithms of Annual Dungeness Crab Prices and Quantities, 1950-2002

State	Mean	Standard Deviation	Coefficient Variation	Minimum	Maximum
		Quantity (lbs)			
Alaska	15.52	0.67	0.18	13.22	16.57
Washington	16.07	0.53	0.14	15.19	17.13
Oregon	15.92	0.49	0.12	14.63	16.81
California	15.88	0.75	0.19	13.44	17.33
		Price (cents/lb)			
Alaska	3.61	1.19	0.33	1.61	5.41
Washington	3.88	1.07	0.28	2.09	5.37
Oregon	3.90	1.08	0.28	2.08	5.36
California	4.00	1.02	0.26	2.15	5.54

II.3 Models and Methodologies

II.3.1 Vector Error Correction Model (VECM)

Empirical economics does not suggest a prior structure for the causality among the four-state Dungeness crab's landing prices and quantities. Therefore, if some series in the evaluated price and quantity data are non-stationary and cointegrated, the error correction framework is viewed as the basic and useful tool for analyzing the above dynamic relationship. The VECM framework is well-developed by Engle and Granger (1987), Hansen and Juselius (1995), Jonathan (2006), Juselius (2006):

II.(1) $\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \mu + e_t \;\; (t = 1, \dots, T)$

where ΔY_t is the first differences ($Y_t - Y_{t-1}$), Y_t is a $(m \times 1)$ vector of the four-state price and quantity variables at the time t (m=8 in this study), Π is a (8×8) matrix of coefficients relating the lag of the variables in levels to current changes in variables, Γ_i is a (8×8) matrix of coefficients relating the i-period lagged variable changes to current changes in variables, μ is a (8×1) vector of constant, and e_t is a (8×1) vector of a number N of independent, identically distributed (i.i.d) innovations (i.e., error terms). Π has reduced rank and can be represented as $\alpha\beta'$, where α and β are $8 \times r$matrices of full rank, and r, a positive number less than or equal to the number of series, is defined as the rank of Π (i.e., the number of cointegration relationships).

Various procedures have been widely used to determine cointegrating rank such as Johansen's trace test (Juselius 2006), Schwarz information criterion (Phillips 1996; Wang and Bessler 2005) and Hannan and Quinn (HQ, 1997) information criterion and so on. The trace test requires two steps: the trace test for the cointegration vector being identified posterior to the selection of the lag length in a vector autoregression (VAR). While, by minimizing the information criteria, the researchers are allowed to jointly determine the lag length and the cointegrating rank over a pool model with various lag lengths and cointegrating ranks (Wang and Bessler 2005). In fact, the VECM has been used in practice for extrapolating past economic behavior into the future (i.e., forecasting). Unfortunately, the above tests and information criteria used to determine the number of cointegrating vectors is not mainly based on examination of the out-of-sample forecasting performance and thus likely yield problems with forecasting accuracy. The VECM models with various lag lengths or/and various cointegrating ranks may have different predictive performances. We introduce and apply the two methods considering forecast performance to select the number of cointegrating vectors: the forecast procedures (Kling and Bessler 1985) and the conjecture model (Bessler and

Wang 2012). In order to best describes and fits the Dungeness crab data using the VECM model, the results from the two forecasting models and those from the three frequently used methods are all compared to determine the number of cointegrating ranks.

Kling and Bessler's 1985 forecast procedures require two subsamples of data (i.e., within-sample and out-of-sample data) and then compares the out-of-sample forecast results for the variations (e.g., the VECM models with different ranks) on the basis of root mean square (RMS) error and ln determinant. In this study, the forecasts for each series with one through eight cointegrating ranks are examined in accordance with RMS; and as an overall measure for the VECM model with each rank, the ln determinant of the covariance matrix of forecast errors is evaluated. The second procedure of determining the rank of Π used in this study is the conjecture model as defined by Bessler and Wang (2012):

> Definition: "Scientists implicitly seek a model, theory, or explanation whose forecasts d-separate predictions that are derived from inferior models, theories, or explanations and Actual realizations of the world" (Bessler and Wang 2012).

The conjecture model assumes that the Actual realization come in real time after any forecasts, so the information flow flows from the Actual never come back to any forecast. Here, several sets of forecasts on each series emanate from the VECM models with the same data but with different ranks of Π. Then, we test the hypotheses that the information links among data forecasts from the model with different cointegrating ranks and the Actual realization of the variable of interest. D-separation (described later) offers a succinct notion to illustrate that one set of forecasts dominates over the other sets on each series, and the dominating set whose rank is selected as the candidate for the number of the cointegrating vectors. Actually, the series may have different candidates so that the most frequent number among the candidates of all the series is the best choice for the number of cointegrating ranks used in the VECM model.

Through the parameters in equation II.(1), the VECM can be composed of three-part information: the long-run, short-run and contemporaneous structure. The long-run structure can be identified through testing hypotheses on the parameter β, while hypotheses on the parameters α and Γ_i are related to the short-run structure (Hansen and Juselius 1995; Juselius 2006). Furthermore, the contemporaneous structure can be summarized through structural analysis of e_t (Swanson and Granger 1997). We examine tests of hypotheses on the cointegration space including test for exclusion and test for weak exogeneity.

The test of exclusion provides useful information on whether each price and quantity series enters all of the identified long-run relationships. The null hypothesis is that each series is not in the cointegration space or alternatively stated, $\beta_{ij} = 0$, for $i = 1,\ldots,8$ and $j =1,\ldots,r$ (Hansen and Juselius 1995). Under the null, the test statistic is asymptotically distributed as chi-square with r degrees of freedom. The test of weak exogeneity examines whether each series does not react to the long-run disequilibrium. Under the null hypothesis that $\alpha_{ij} = 0$, for $i = 1,\ldots,8$ and $j =1,\ldots,r$, the test statistic is distributed as chi-square with degree of freedom equal to the number of the rank of Π (Hansen and Juselius 1995).

It is difficult to make sense of the coefficients of the VECM (Sims 1980). Accordingly, innovation accounting technique may be the way to describe the dynamic structure and the interactions among the time series (Sims 1980; Lütkepohl and Reimers 1992; Swanson and Granger 1997). Here, the estimated VECM is algebraically converted to a levels VAR. The innovation accounting based on the equivalent levels VAR is then generated to summarize the dynamic interaction among the price and quantity series. The forecast error variance decompositions over a variety of horizons are shown in this study.

Swanson and Granger (1997), Spirtes, Glymour and Scheines (2000), Hoover (2005), and Hyvärinen et al. (2010) suggest that the information on the causal relationships among innovations in contemporaneous time can be examined based on the information of the error terms in the autoregressive models. The DAGs are used in this paper to obtain data-determined evidence on the contemporaneous causal ordering, under the assumption that the information set is causally sufficient (Spirtes, Glymour, and Scheines 2000; Shimizu et al. 2006; Pearl 2000; Hoyer et al. 2008). A Bernanke ordering dealing with contemporaneous innovation is based on the discovered structure from the DAGs (Swanson and Granger 1997).

II.3.2 Directed Acyclic Graphs (DAGs)

DAGs contain vertices, edges, and arrowheads but no self-loops and no directed cycles to provide an illustration of causal relationships among a set of variables (Pearl 2000). Recently, under different assumptions of the data (i.e. the statistical properties of the data) and in different ways, several methods such as the linear-Gaussian approach[8] (Spirtes, Glymour, and Scheines 2000; Pearl 2000), linear-non-Gaussian approach (Shimizu et al. 2006), and combination of the two above approaches (Hoyer et al. 2008) have been developed to discover the acyclic causal structure of the observational data. A key difference among these three approaches is the assumption of Gaussian/ non-Gaussian/ partial Gaussian innovations. Causal diagrams for empirical studies may be biased and unreliable when the innovations are departing from the assumptions of the used approaches. The study diagnoses the distribution of innovations and subsequently selects and compares the well-suited algorithms of DAGs to understand the price-quantity relationships of the four Dungeness crab landing markets. The followings are the basic concepts, assumptions, applications of the three approaches:

II.3.3 Linear-Gaussian Acyclic Approach

Under the assumption of Gaussianity of disturbance variables, several authors (Spirtes, Glymour, and Scheines 2000; Pearl 2000) use DAGs for the purpose of discovering conditional independence relations in a probability distribution. That is, an assumption of Gaussianity which means an unskewed distribution (i.e., a symmetric distribution) allows that conditional correlation can be completely estimated just from the covariate matrix (i.e., second-order statistics) but not from higher-order moment structure. This line of research implies that the conditional independence cannot separate between independence-equivalent models. Mathematically, the Gaussian DAG models

[8] The term "linear-Gaussian approach" is defined by Shimizu et al. (2006).

represent conditional independence as implied by the recursive production decomposition:

II.(2) $Pr(v_1, v_2, \dots, v_n) = \prod_{i=1}^{n} \Pr(v_i | pa_i),$

Where Pr denotes the probability of variables (i.e., vertices) v_1, v_2,…, v_n, pa_i is the realization of some subset of the variables that precede v_i in order (i=1,2,…,n), and the symbol Π is the product (multiplication) operator. Pearl (2000) proposes d-separation (i.e., direct-separation viewed as a graphical characterization of conditional independence shown in equation II.(2). If the information between two vertices (for example, variables X and Y) is block, the information is said to be d-separation from the one variable (X) to the other variable (Y). That is, the d-separation occurs if (i) a fork chain $X \leftarrow Z \rightarrow Y$ or a causal chain $X \rightarrow Z \rightarrow Y$ exists such that the middle variables Z is in the information; or (ii) an inverted fork $X \rightarrow Z \leftarrow Y$ exists such that the middle variable (a collider) Z or any of its descendent is not in the information.

If we formulate a DAG in which the variables (v_1, v_2,…, v_n) corresponding to pa_i are illustrated as the parents (directed cause) of v_i, then the independencies applied by equation II.(2) can be read off the graph using the d-separation criterion. Geiger, Verma and Pearl (1990) revealed that there is a one-to-one correspondence between the set of conditional independencies, $X \perp Y | Z$, implied by equation II.(2) and the set of triples (X, Y, Z) that satisfy the d-separation criterion in graph G. Specifically, suppose that G is a DAG with variable set V in which X and Y as well as Z exist, then G linear implied the zero correlation between X and Y conditional on Z if and only if X and Y are d-separation given Z.

Several alternative algorithms learning the DAGs from the Gaussian distributed data have been studied for decades, but two alternative algorithms based on either conditional independence constraints or Bayesian scoring criterion are often used and compared with each other (e.g., Wang and Bessler 2006; Kwon and Bessler 2011). That is, in both of the frameworks that the algorithms are used to obtain the DAGs from the variance/covariance matrix with VECM innovations under Markov condition (i.e., acyclic and causal sufficiency condition), and faithfulness assumptions[9], the PC algorithm (Spirtes, Glymour, and Scheines 2000) relies on constraint-based test while the GES algorithm (Chickering 2002) search the space of models using a score.

The PC algorithm starts systematically from a completely connected undirected graph G on the set of variables to be determined. Edges between variables are removed sequentially based on zero unconditional correlation and partial correlation (conditional correlation) at some pre-specified significance level of normal distribution. *The conditioning variable(s) on the removed lines between two variables is called the sepset, as defined in Bessler and Akleman (1998), of the variables whose line has been removed (for vanishing zero-order conditioning information the sepset is an empty set).* For a simplified example of triples X−Y−Z, X−Y−Z can be directed as an inverted fork X→Z←Y if Z is not in the sepset of X and Y (that is, the zero unconditional correlation between X and Y). If the correlation between X and Y conditional on Z is zero, the

[9] According to Kwon and Bessler (2011), the causal Markov condition which consists of acyclic and causal sufficiency (i.e, mutual independent error terms or the assumption of no latent variables) is assumed in most empirical studies, although using the condition can be problematic. The faithfulness assumption is that all the (un)conditional probabilistic structures are stable (i.e. faithful or a DAG-isomorphism) with respect to changes in their numerical value.

underlying model may have been a fork chain X ← Z → Y or a causal chain X → Z → Y. Hence, the edge between X, Y and Z would not be directed so that the undirected edges X−Z−Y would be left under the PC algorithm.

At small sample size, the PC algorithm may erroneously add or remove edges and direct edges at the traditionally applied significance level (e.g., 0.1 or 0.05). Monte Carlo studies with small sizes has been well discussed in Spirtes, Glymour, and Scheines (2000, pp. 116): "In order for the model to converge to the correct decisions with probability 1, the significance level used in making decisions should decrease as the sample sizes increase, and the use of higher significance levels (e.g., 0.2 at the sample sizes less than 100, and 0.1 at sample sizes between 100 and 300) may improve performance at small sizes." The PC algorithm would be applied at the significance level of 0.2 in this study due to our sample sizes less than 100.

The GES algorithm is a two-phase algorithm that searches over alternative DAGs using the Bayesian information criterion as a measure of scoring goodness fit. The algorithm begins with a DAG representation with no edges. A DAG with no edges implies independence among all variables. Edges are added and/or edge directions reversed one at a time in a systematic search across classes of equivalent DAGs if the Bayesian posterior score is improved. The first stage ends when a local maximum of Bayesian score is found such that no further edge additions or reversal improves the score. From this final first stage DAG, the second stage commences to delete edges and reverse directions, if such actions result in improvement in the Bayesian posterior score. The algorithms terminates if no further deletions or reversals improve the score.

II.3.4 Linear-Non-Gaussian Acyclic Model (LiNGAM)

Even though linear-non-Gaussian acyclic Model (LiNGAM) is not employed in this study, it is an important part to form the PC-LiNGAM algorithm. The brief introduction to LiNGAM is interpreted as follows.

When the Markov condition and the assumption of non-Gaussian innovations are both valid[10], the LiNGAM allows the complete causal structure of the non-experimental data to be determined without any prior knowledge of network structure (such as a causal ordering of the variables). Here, the non-Gaussian structure may provide more information than the covariance structure which is the only source of information in the linear-Gaussian acyclic approach. The first algorithm for LiNGAM, ICA-LiNGAM proposed in Shimizu et al. (2006), is closely related to independent component analysis (ICA) (Hyvärinen, Karhunen, and Oja 2004) and is applicable to purely non-Gaussian data. The key to the solution of the ICA-LiNGAM algorithm is to realize that the observed variables are linear functions of the mutually independent and non-Gaussian innovations. Details on the process of the ICA-LiNGAM model identification are given in Shimizu et al. (2006, pp. 2006-2008). It is worthy noting that the ICA-LiNGAM algorithm is inapplicable to data which is partially Gaussian (Hoyer et al. 2008) or which has more than one Gaussian distributed series (Hyvärinen et al. 2010).

[10] The algorithm with the three assumptions is called LiNGAM: (1) the recursive generating process, (2) the linear data generating process, (3) mutually-independent and non-Gaussian innovations with arbitrary (non-zero) variances. Note that the recursive generating process means the graphic representation by DAGs; the independence of the innovations implies non-existence of unobserved confounders or the causally sufficiency. Also note that LiNGAM does not require the faithfulness (or stability) of generating model. See Shimizu et al. (2006, pp. 2004-2005) for details on the LiNGAM assumptions and properties.

II.3.5 Combination of the Gaussian and Non-Gaussian Approaches

PC-LiNGAM algorithm (Hoyer et al. 2008) combines the strengths of the approaches purely based on conditional independence and those of the ICA-based methods. An important goal in the algorithm is to show the distribution-equivalence patterns that identify DAGs in mixed Gaussian/ non-Gaussian models[11]under the Markov condition and the faithfulness assumption. The PC-LiNGAM algorithm consists of three stages: First, the PC algorithm is used to obtain the d-separation equivalence class. Second, all DAGs in the first-stage estimated equivalence class are scored using the ICA objective function[12], and then the highest-scoring DAG (i.e., the DAG with least dependent estimated innovations) is selected. The third step identifies the correct distribution-equivalent class: construct equivalence-class based on the estimated DAG and the results of the tests for Gaussianity for the estimated innovations.

The four algorithms discussed here including PC, GES, ICA-LiNGAM, and PC-LiNGAM algorithms are available under the Tetrad project at Carnegie Mellon University. We conduct the four algorithms, generate several DAGs, and then select the

[11] The PC-LiNGAM algorithm does not require the Gaussian nor non-Gaussian distributed innovations.

[12] The ICA objective function U , as a measure of the non-Gaussianity of a random variables, is shown in Hoyer et al. (2012) :

$$U = \sum_i (E\left\{|e_i| - \sqrt{2/\pi}\right\})^2 ,$$

where e_i are the mutually-independence innovations with arbitrary densities. The function can be shown to provide a consistent estimator for searching the independent components under the weak conditions. However, it has two limitations: First, the disregarded sampling effects may lead that distribution-equivalent models obtain exactly the same value of U. However, the practical case of a finite sample is not the case because the correct distribution-equivalent class is identified in the final stages of the PC-LiNGAM algorithm. Second, the objective function may mislead due to the linear correlation among the estimated innovations.

best-described causal structure among these DAGs to represent the price-quantity relationships of the four Dungeness crab markets.

II.4 Empirical Results

All estimations are carried out in terms of the natural logarithms of the price and quantity series. The first 53 observations (within-sample data) are first considered to the time series properties of the VECM model, while about 16% of the entire data is reserved so they can be used for out-of-sample forecasts to determine the number of cointegrating vectors.

In order to determine whether the VECM model is appropriate for the Dungeness crab landing price and quantity series, the two unit root tests on the levels of the within-sample data are applied: Phillips and Perron (1988) and Augmented Dickey-Fuller (ADF,1981) tests. The Bayesian information criterion (BIC) is conducted as a selection criterion to select the appropriate lag lengths contained in the ADF test with a maximum of four lags. Results of the both tests are the same shown in table II.2. Each state's price series is non-stationary at the 5% significance level. Moreover, the null hypotheses of non-stationarity for the Alaska, Oregon and California quantity series are rejected, but the tests fail to reject the null hypothesis for the Washington quantities. Although the Washington quantity series is non-stationary at the 5% significance level, the t-statistics

(-2.67) appears to be close to the critical value of -2.92[13]. The following phenomena may contribute to these stationary quantity series. The Dungeness crab catch records along the Pacific Coast vary in a cyclic pattern (Botsford et al. 1998). The crab abundance peaks in around 10-year cycles (Dewees et al. 2004). Nevertheless, the two unit root tests show at least two series in the evaluated data are non-stationary, thus a multivariate cointegration model is appropriate (Hansen and Juselius 1995).

Table II.2. Unit Root Tests on Levels of Log Quantity and Price Series

Series	Philips-Perron Test	Augmented Dickey-Fuller Test
Log Alaska Quantity (LAKQ)	-3.21	-3.15 (0)
Log Alaska Price (LAKP)	-1.23 *	-1.21 (0) *
Log Washington Quantity (LWAQ)	-2.72 *	-2.67 (0) *
Log Washington Price (LWAP)	-0.77 *	-0.75 (0) *
Log Oregon Quantity (LORQ)	-4.30	-4.22 (0)
Log Oregon Price (LORP)	-0.96 *	-0.94 (0) *
Log California Quantity (LCAQ)	-3.44	-5.19 (2)
Log California Price (LCAP)	-1.10 *	-1.08 (0) *

Note: Numbers in parentheses are the lags included in ADF test to reach a minimum BIC.
"*" means the series is non-stationary at 0.05.

[13] The Washington quantity series is not non-stationary at the 10% significance level since the t-statistics is less than the critical level of -2.60.

The appropriate lag length (k) in the VECM model of the equation II.(1) is one, chosen on the basis of the BIC with a maximum of four lags. Previous studies have determined the number of cointegrating vectors using the trace test, the Schwarz information criterion, and the HQ loss measures. All the three tests for determining the number of cointegrating ranks for both[14] no constant within (a constant outside) and linear trends within the cointegrating vectors are conducted in this study with the CATS in RATS program. It is noticeable that the CATS calculates the rank test statistics for the VECM model at each level of cointegration but excludes the statistics for zero rank (no cointegrating vector). Following the sequential testing procedure of the trace test (Hansen and Juselius 1995), table II.3 is read from left to right and from the top to bottom. The first failure to reject the null hypothesis in this sequence is less or equal to two in the case of a constant outside the cointegrating space. Figure II.2 shows plots of both the Schwarz and HQ loss measures at each level of cointegration for the zero constant or the linear trends inside the cointegrating vectors. Generally, the Schwarz measure fits the same or lower order than HQ measure. The Schwarz measures are minimized at one rank with the constant outside the cointegration space; while the HQ measures reach minimum at two ranks with the trend inside the cointegration space. Unfortunately, the three rank-based tests determine the three combinations (different

[14] The CATS are used to conduct the four VECM models with the different assumptions about the constant term and linear trends (Hansen and Juselius, 1995): (1) the model with neither the constant nor trends; (2) the model restricting the constant to the cointegration space; (3) the model having a constant outside the cointegration space; (4) the model with the linear trends inside the cointegration space. The VECM model without any deterministic components should be used carefully because at least a constant is very likely in the cointegration space. The VECM model with a constant within the cointegration space does not fit the Dungeness crab data well. Hence, we consider the last two models.

ranks with different components inside the cointegration relations). In many empirical studies, the VECM model with the trends inside the cointegrating vectors is rarely applied. Besides, the results of both the trace test and the Schwarz measure support no constant in the cointegraiton space, which would be imposed on the model of the Dungeness crab's landing markets.

Table II.3. Trace Tests of Cointegration among Logarithms of Dungeness Crab Quantities and Prices

H_0:Rank	No Constant within the Cointegrating Vectors			Linear Trend within the Cointegrating Vectors		
	Trace[a]	C(5%)[b]	Decision	Trace[a]	C(5%)[b]	Decision
$r = 0$	189.47	155.75	Reject	216.23	182.45	Reject
$r \leq 1$	128.04	123.04	Reject	154.69	146.75	Reject
$r \leq 2$	84.85	93.92	Fail*	105.63	114.96	Fail
$r \leq 3$	54.25	68.68	Fail	73.82	86.96	Fail
$r \leq 4$	32.35	47.21	Fail	46.09	62.61	Fail
$r \leq 5$	19.60	29.38	Fail	24.27	42.20	Fail
$r \leq 6$	9.77	15.34	Fail	11.83	25.47	Fail
$r \leq 7$	0.75	3.84	Fail	2.65	12.39	Fail

[a] Trace refers to the trace statistic considering the null hypothesis that the rank of Π is less than or equal to r.
[b] C(5%) refers to the critical values at the 5 percent level. If the trace statistics exceeds its critical value, the null hypothesis is rejected.

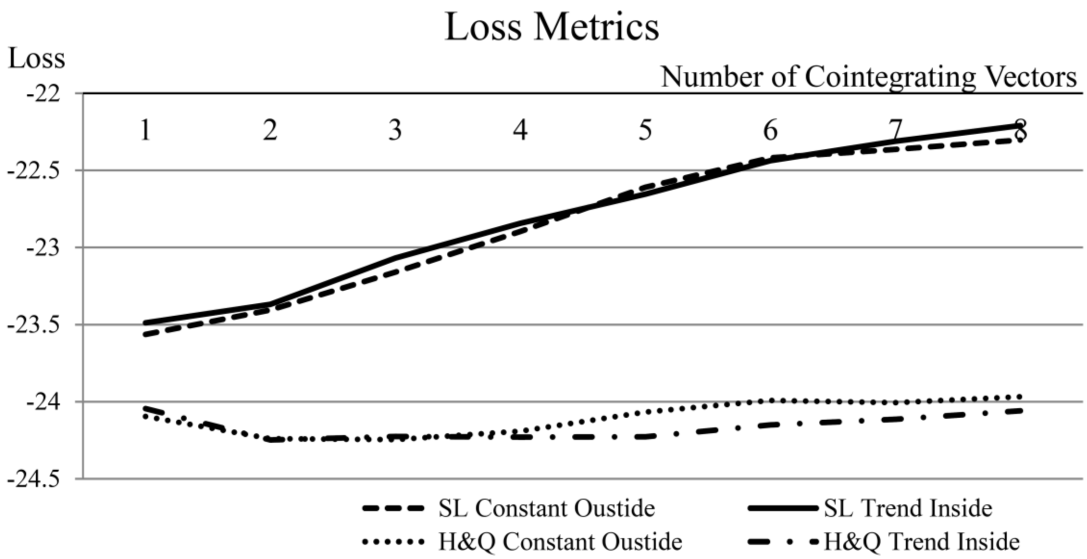

Figure II.2. SL and HQ Statistics for Different Numbers of Cointegrating Rank in VECM Model with the Constant Outside and the Trends inside the Cointegration Space

Unlike the three tests without consideration of the out-of-sample forecast, the RMS error, the ln determinant, and the conjecture model are also used to select the number of cointegrating vectors. The two-step procedure is used. First, the forecast statistics of the RMS error and the ln determinant are calculated (in RATS). Figure II.3 ranks the VECM model with different numbers of cointegrating vectors according to ln determinant and RMS error at the one-step ahead. The RMS errors are useful for evaluating the forecast performance of the individual price/quantity series with zero through eight cointegrating vectors. For the Alaska price and quantity series, one cointegrating vector performs best. Zero cointegrating vectors appear to be best suited in the Washington price and quantity, and the Oregon and California price equations respectively. Both the Oregon and the California quantity series rank the five cointegrating vectors first. One way to obtain a rough determination of the number of cointegrating vectors in the overall VECM model (not in the individual equations), is to average the best-performing numbers of cointegrating vectors across the eight series. The number is 1.5 and this implies that one or two cointegrating vectors may provide the best forecasts, providing the best overall performance of the model. With respect to the ln determinant measures, zero cointegrating vector performs best, followed by one cointegrating vector. By combining both the RMS and ln determinant results, the VECM model with zero, one, or two cointegrating vectors (the three sets) may perform better than the models with the other numbers.

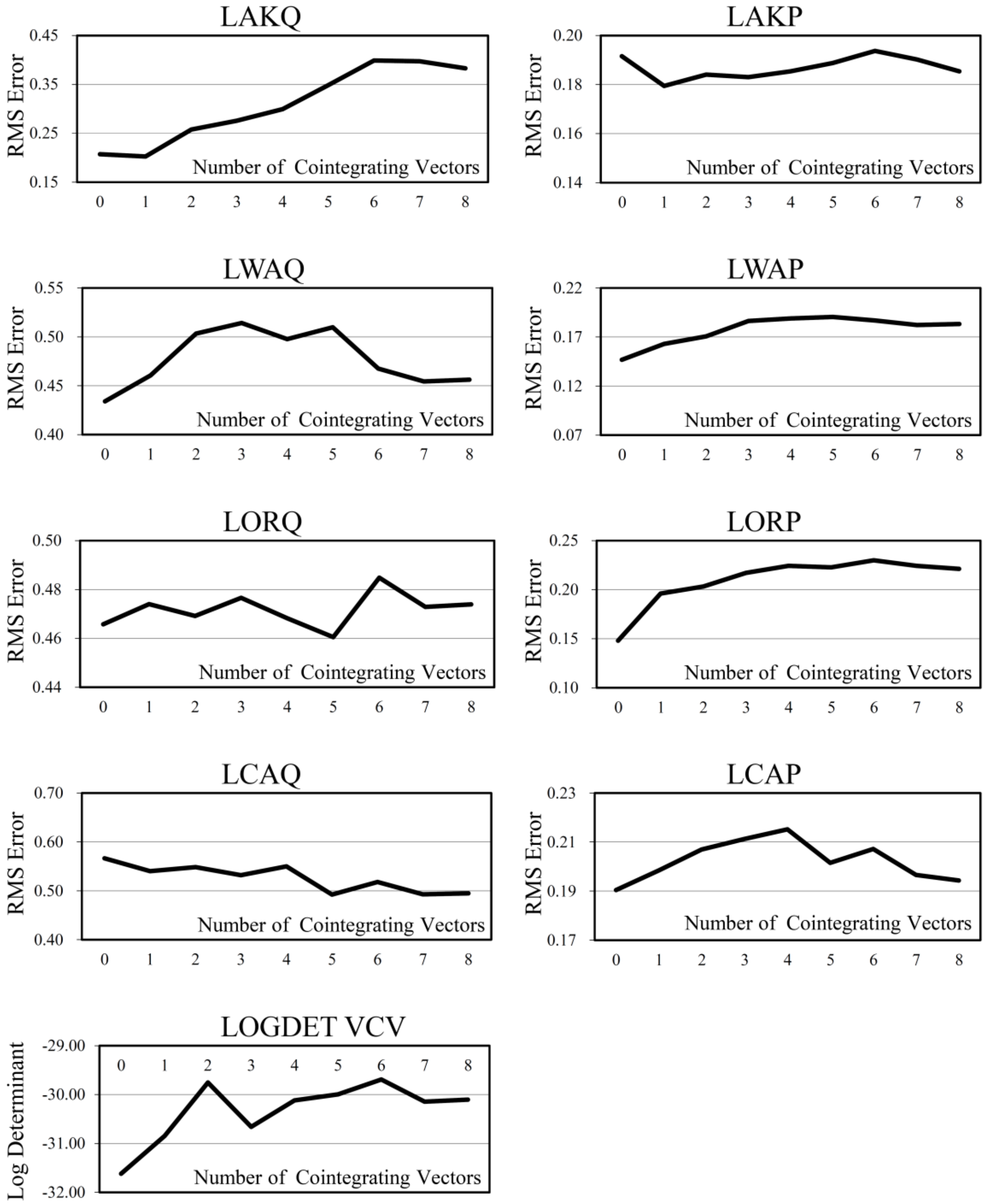

Figure II.3. RMS Errors of Logarithms of Dungeness Crab Quantities and Prices and Log Determinant

The second step is to search among the three sets using the conjecture model to find the best. That is, the GES algorithm[15] assesses the “causal” relationships among these three sets of cointegrating vectors for generating price/quantity forecasts and Actual prices/quantities (the out-of-sample data) subject to the restriction that the Actual is unable to affect the forecasts. The patterns for one-step ahead are summarized in figure II.4. The forecasts from the one cointegrating vector directly arrow toward the Actual level for the Alaska price and quantity respectively, While the forecasts from the zero cointegrating vector is of high quality in the Washington and Oregon price series. Obviously, the forecasts from the zero or one cointegrating vector are the most common direct cause of the Actual data, and the probability of choosing both by the price/quantity series is 50% respectively.

If the results from the three forecasting tests and the three traditional ranked-base ones are all considered, half of these tests (the Schwarz measures, ln determinants measure, and conjecture model) select the one cointegrating rank. Hence, one may expect to see this one cointegrating vector with the constant outside the cointegration space among the four states’ Dungeness crab price and quantity series.

[15] GES algorithm and PC algorithm, as provided in the TETRAD umbrella, allow researchers to apply Knowledge tiers that prevent the Actual from cause the forecasts. Since the GES algorithm provides more information on the causal relationships than the PC algorithm here, the patterns of the GES algorithm are shown in this study.

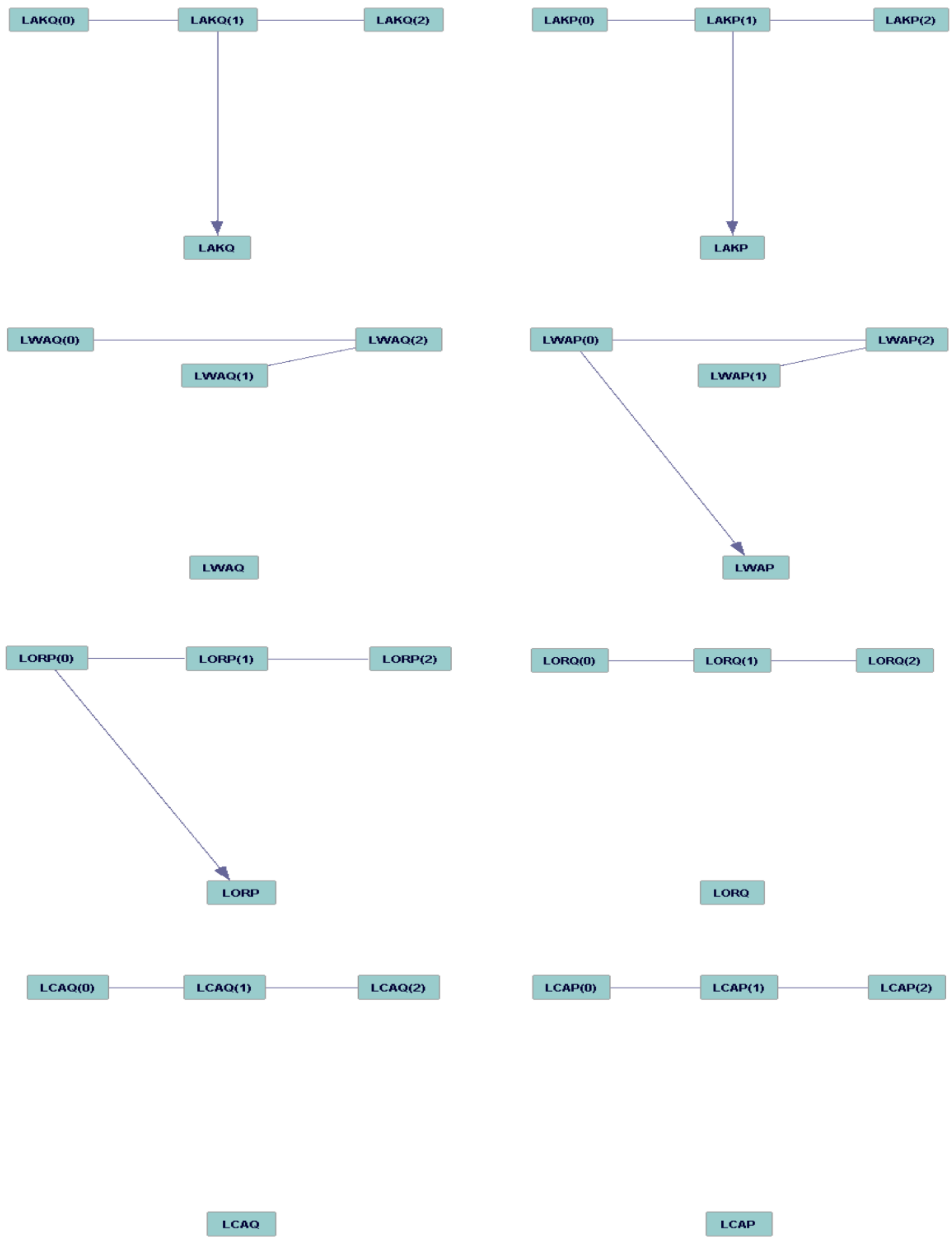

Figure II.4. Patterns from GES Algorithm on Forecasts of Series and Actual, 2003-2012

Notes: Numbers in parentheses are the number of cointegrating vectors.

Before discovering the price-quantity causal structure of the Dungeness crab, we need to understand the statistical properties[16] of the innovations and tests for stationary, exclusion and weak exogeneity. For the case with the single cointegrating rank, Lagrangian Multiplier tests (Hansen and Juselius 1995) on first and fourth order autocorrelation cannot be rejected at usual levels of significance. In facts, we reject first order autocorrelation at a p-value of 0.13 and four order autocorrelation at a p-value of 0.43. The four moments of the innovations of each series including mean, standard deviation, skeweness and kurtosis are shown in table II.4. Based on the skewness and kurtosis of multivariate innovations, Doornik-Hansen test (2008) examines the null hypothesis of the multivariate normal innovations. The innovations with one cointegrating vector (the *p*-value of 0.041) is normal distributed at the 1% significance level but is not at the 10% or 5% significance level. The choice of the different significance levels (α=1%, 5%, or 10%) decides either the normality of the innovations or the non-normality of the innovations. The univariate normality tests for the eight series in table II.4 show that more than one of the innovations are normal at the 1%, 5%, or 10% levels, suggesting that the LiNGAM algorithm is unable to employed in this study. To avoid losing information from this type of the innovations, the PC, GES, and PCLiNGAM algorithms are all used to search the causal relationship among the four Dungeness crab landing markets.

[16] The univariate statistics for the estimated residuals of each equation obtained by CATS in RATS differ from those obtained by RATS' STATISTICS instruction (Jonathan, 2006). Moreover, CATS in RATS does not provide the statistical measures for the VECM model with zero rank. For these reasons, the statistical properties of the model are executed by RATS.

Table II.4. Descriptive Statistics for the Innovations, 1950-2002

Variables	Mean	Standard Deviation	Skewness[a] (p-value)	Kurtosis[b] (p-value)	Normality[c] (p-value)
LAKQ	0.00	0.54	0.34 (0.33)	1.43 (0.05)	6.23 (0.04)
LAKP	-0.00	0.28	0.27 (0.43)	1.24 (0.09)	5.29 (0.07)
LWAQ	-0.00	0.38	0.10 (0.78)	0.33 (0.65)	1.20 (0.55)
LWAP	-0.00	0.20	0.46 (0.19)	0.46 (0.52)	2.27 (0.32)
LORQ	-0.00	0.47	-0.11 (0.75)	0.05 (0.95)	0.44 (0.80)
LORP	0.00	0.20	-0.16 (0.65)	-0.56 (0.44)	0.73 (0.70)
LCAQ	0.00	0.63	-0.34 (0.33)	1.25 (0.09)	5.21 (0.07)
LCAP	0.00	0.24	0.13 (0.71)	0.18 (0.81)	0.75 (0.69)

Note: See table II.2 for the definition of variables. The four moments and normality test of the innovations of each series from the VECM model are estimated using RATS.
[a] The null hypothesis of skewness tests states that skweness of each series is zero.
[b] Kurtosis tests are related to the null hypothesis of kurtosis of each series being zero.
[c] Doornik–Hansen univariate normality tests consider the null hypothesis that each series has normal distribution. The results show that Alaska price and Quantity and California quantity are not normally distributed at the 0.1 level while the other series are normal.

Given this single cointegrating vector, some exploratory tests on the long-run interdependence among these eight price/quantity series are further conducted. First, we explore the possibility that a long-run relationship (cointegrating vector) arises because one or more of the series is itself stationary, especially since the ADF test suggests that the three quantity series are potentially stationary (Alaska, Oregon, and California Quantity see table II.2). As presented in table II.5, the null hypothesis that each series is itself stationary in the cointegration space is clearly rejected at very low *p*-values. The test results suggest that the one cointegrating vector arises from a linear combination of the eight individual series.

Table II.5. Test for Stationary of Levels, Exclusion from the Cointegration Space, and Weak Exogeneity Test

Series	Test		
	Stationary[a], df=7	Exclusion[b], df=1	Weak Exogeneity[c], df=1
LAKQ	49.44	0.08	1.10
LAKP	58.98	6.02	0.02
LWAQ	53.13	13.70	2.59
LWAP	59.74	0.01	1.70
LORQ	41.50	8.31	4.28
LORP	59.49	17.97	8.17
LCAQ	48.45	0.85	3.12
LCAP	59.19	11.76	0.94
Critical (5%)	14.07	3.84	3.84

[a]Stationarity tests are on the null hypothesis that the series listed in the column heading is one of the one stationary relationships found in figure II.4.
[b]Exclusion tests are related to the null hypothesis that the series is not in the cointegration space.
[c]Weak exogeneity tests consider if the series does not respond to the perturbations in the cointegration space.

Exclusion and weak exogeneity test results are also shown in table II.5. In the exclusion test, we consider the possibility that a particular series of the eight series is not in the cointegrating space. Except for the Alaska and California quantities and the Washington price, the null hypotheses associated with the other five series are rejected at the 5% significance level, suggesting they are part of the long-run relationship. The tests of weak exogeneity explore the possibility that some series do not respond to perturbations in the long-run equilibrium (cointegrating vector). From the table we do not reject the null hypotheses for the other six series, except for the Oregon price and quantity. This suggests that the Oregon price and quantity are the only two series to make adjustment toward the estimated long-run equilibrium when the perturbations happen.

Applied to the innovations, the contemporaneous causal relationships from the GES, PC, and PC-LiNGAM algorithms are shown in figure II.5. The results from the PC algorithm at the significance level of 0.2 (figure II.5A) indicate that the double-headed arrow exists between the Washington and Oregon Quantities. Such an arrow is the result of a partial failure of the PC algorithm under violation of its assumptions, and then the 0.05 significance level is used to replace the 0.2 level. Among these DAGs in figure II.5, the DAG using the GES algorithm has the lowest BIC score, followed by the PC-LiNGAM or PC algorithms using the 0.2 significance level. It seems that the GES algorithm performs best, but represents the undirected relationships (e.g., the undirected edges) among the four states' Dungeness crab prices and quantities (figure II.5B). Such undirected edges also exist in the DAG with the PC algorithm (figure II.5C). Clearly, the Alaska price, the Washington price, the Oregon price, the California price, and the California quantity are linked but the causality is unknown. To determine the causal relationships among the linked but undirected series in figure II.5C, the PC-LiNGAM algorithm is employed and a causal chain from the Alaska price to the California quantity through the Washington, Oregon, and California prices is determined (figure

II.5D). Hence, the figure II.5D is the finalized DAG depicting the contemporaneous relationships among the four states' prices and quantities.

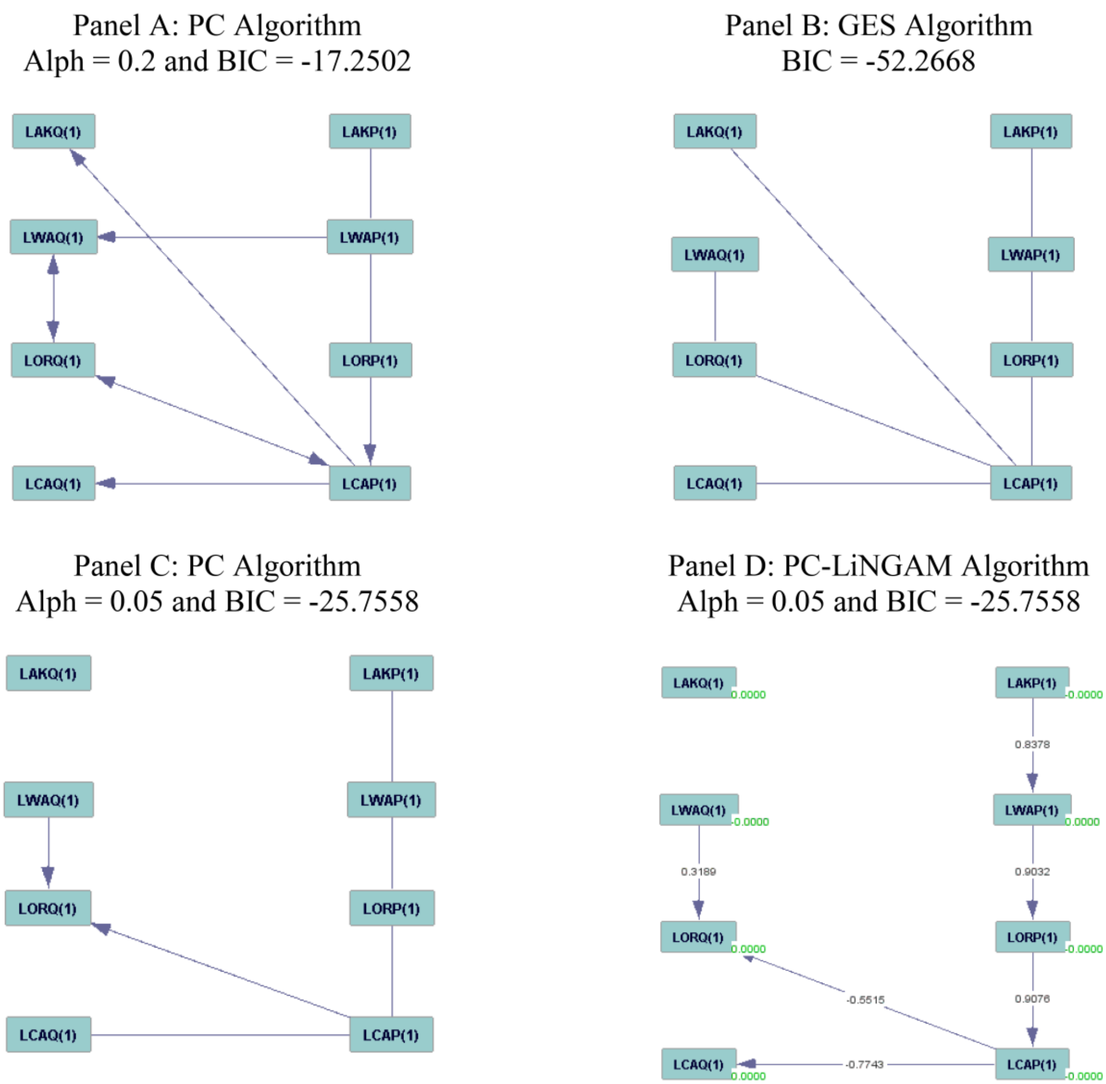

Figure II.5. Patterns of Causal Flows among the Four States' Dungeness Crab Markets
Note: Pattern finally determined using PC-LiNGAM algorithm in Tetrad V (2014). Numbers in parentheses are the number of cointegrating vectors.

More interestingly, some of the results obtained from the PC-LiNGAM algorithm are consistent with the literature on the Dungeness crab movement patterns and the actual findings. First, considering the relationship of the four state's Dungeness crab landing quantities (especially for sexually mature male), the figure II.5D clearly shows there are no directed edges between the states which are not adjacent to each other. That is, from an ecological perspective, the results suggest that the adult male Dungeness crab in the one state is unable to move across the neighboring states to the other state (i.e., the Oregon (Alaska) crab cannot migrate to Alaska (Oregon)). Combination of the information on the length of each state's coastline and the literature on the Dungeness crab movement (i.e., Stone and O'Clair 2001) implies that the crab cannot move to the unadjacent states. Second, the Alaska quantity is not linked to the other prices and quantities. This may result from the Alaska Dungeness crab stock collapse[17] and different crabbing seasons throughout Alaska.

Figure II.5D clearly shows that the four states' Dungeness crab prices are strong connected in contemporaneous time, and are determined by the PC-LiNGAM as a causal chain from the Alaska price to the California price through the Washington and the Oregon prices. Here, the Alaska price and the Washington quantity are both the information initiator in the Dungeness crab markets, while the other three states' prices

[17] The fisheries for Dungeness crab have historically occurred throughout the Alaska coast, but several stocks in the Alaska such as Prince William Sound, Copper River delta, and Kachemak Bay area have collapsed. The possible causes of these collapses include overfishing, sea otter predation, and adverse climatic changes. The Dungeness crab fishery in Yakutat has been close since 2001 due to the stock collapse in 2000. In contrast, Southeast Alaska and the Kodiak area remain open to support mainly small boat fisheries with harvests fluctuating. See Woodby et al. (2005) for the Alaskan Dungeness crab fishery.

(excluding the Alaska price) and the California and Oregon quantities receive information. The tri-state Dungeness crab committee[18] including Washington, Oregon, California was formed in 1998 to devote the three states' management of Dungeness crab. This suggests that the price and quantity relationships among the three states' markets should exist. Such relationships shown in figure II.5D are described below.

The Washington quantity actively generates information and passes it to the Oregon quantity within a year. The Oregon and California quantities are information "sinks." That is, the Oregon quantity receives information from both the Washington quantity and the causal chain of the four states' prices, but does not pass it on other prices and quantities. The California quantity receives information from the causal chain of the prices through the California price. The information flow of the prices (the causal chain) may be blocked on its path to the Oregon and California quantities by the California price. The fact that the California price causes its own quantity suggests that the quantity-dependent function exists in the California Dungeness crab market.

Based on the estimated results of the equation II.(1) together with the causal structure in figure II.5D, the forecast error variance decomposition (table II.6) measures the dynamic interactions among the Dungeness crab price and quantity series. The forecast error in each series is decomposed at horizons of 0 (contemporaneous time), 1, and 10 years ahead. Each sub-panel of the table shows the percentage of forecast error uncertainty (variation) in each series at time $t+k$ that is accounted for by the earlier

[18] The details on Dungeness Crab Conservation and Management Act are available at https://www.govtrack.us/congress/bills/105/s1726/text

innovations in each of the eight series at time *t*. For example, the uncertainty associated with current quantity in Oregon is primarily explained by the current shocks in its own quantity (51.8%), in the Alaska price (17%), and in the Washington quantity (12.1%). When moving ahead one period (one year), the variation in the Oregon quantity is influenced by the shocks its own quantity (35.9%), in the California price (20.8%), in the Alaska price (18.1%), and in the Washington quantity (18.1%). At the ten-year horizon, the California price (29.4%), the Oregon quantity (26.2%), the Washington quantity (22.4%), and the Alaska price (19.5%) all contribute to the variations in the Oregon quantity. Here, all prices provide approximately 36.1% of the uncertainty in the Oregon Quantity in contemporaneous time, and then the uncertainty increase to 45.7% and 50.9% at the longer horizons of one year and ten years respectively. The results suggest that the causal chain of the prices (from the Alaska price to the California price in figure II.5D) has more and more influence on the Oregon quantity when the time period moves ahead. Similar statements can be made based on the other values in table II.6 for the other prices and quantities, especially for the California quantity. On the variation of the California quantity, the explanatory power of shocks in all prices increases from 60% in the current time to 61.6% at the ten-year horizon. That implies that the causal chain of the four prices contributes more to the California quantity for longer time horizons.

Table II.6. Forecasts Error Variance Decomposition of the Eight Series

Horizon	LAKQ	LAKP	LWAQ	LWAP	LORQ	LORP	LCAQ	LCAP
LAKQ								
0	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	97.51	0.00	0.11	0.47	0.74	0.33	0.05	0.78
10	96.73	0.00	0.15	0.62	0.98	0.43	0.07	1.02
LAKP								
0	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.00	99.95	0.00	0.01	0.01	0.01	0.00	0.02
10	0.00	99.93	0.00	0.01	0.02	0.01	0.00	0.02
LWAQ								
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	95.39	0.91	1.44	0.64	0.10	1.51
10	0.00	0.00	94.16	1.16	1.83	0.81	0.13	1.92
LWAP								
0	0.00	70.19	0.00	29.81	0.00	0.00	0.00	0.00
1	0.00	72.23	0.16	24.86	1.07	0.47	0.08	1.12
10	0.00	74.00	0.22	22.03	1.46	0.64	0.10	1.53
LORQ								
0	0.00	17.05	12.08	7.24	51.78	5.48	0.00	6.37
1	0.01	18.07	18.06	3.83	35.89	2.92	0.37	20.83
10	0.01	19.48	22.38	1.07	26.20	0.89	0.53	29.44
LORP								
0	0.00	57.26	0.00	24.31	0.00	18.43	0.00	0.00
1	0.01	60.16	0.80	15.80	5.22	12.18	0.37	5.47
10	0.01	64.46	1.13	10.39	7.42	8.27	0.53	7.78
LCAQ								
0	0.00	28.28	0.00	12.01	0.00	9.10	40.05	10.56
1	0.00	28.27	0.28	7.84	1.86	6.04	36.81	18.90
10	0.00	28.66	0.38	5.35	2.51	4.22	35.49	23.37
LCAP								
0	0.00	47.17	0.00	20.03	0.00	15.18	0.00	17.62
1	0.00	47.23	0.09	16.59	0.57	12.67	0.04	22.81
10	0.00	47.47	0.12	14.67	0.76	11.28	0.05	25.66

Note: See the table II.2 for definition of variables. The entries in this table represent percentages summing to 100 for each row. The uncertainty for the series given in the first column is attributable to the variation in each series listed in the column heading. The numbers 0, 1, and 10 in the first column is for steps ahead.

In contemporaneous time, the Alaska price explains a large part of price and quantity in the four states' landing markets, ranging from 17.1% in the Oregon quantity to 100% in its own price (i.e., the Alaska price is exogenous in contemporaneous time). Beside the Alaska price, a large part of variation in price (quantity) is explained by each market's own price (quantity), ranging from 17.6% in the California price to 100% in the Alaska quantity and in the Washington quantity. Accordingly, both each market's own quantity (price) and the Alaska price are the most important contributors to its own current quantity (price) variability. Both explain more than 60% of the variation in each price (quantity).

When moving from the contemporaneous time to the longer time horizons, the Alaska price become more important because it explains higher percentage of the price and quantity variations. The uncertainty in at least five of the eight prices/quantities explained by the Alaska price varies between 17.0% and 70.19% (excludes the Alaska price itself) at the zero horizon, between 18.1% and 72.2% at the one-year horizon and between 19.5% and 74% at the 10-year horizon. Furthermore, the uncertainty in the Oregon quantity, the Washington quantity accounts for increases from 12.1% in the current time to 22.4% at the ten-year horizon. The California price contributes more to its own price and quantity, and the Oregon quantity at the longer time horizons. Next, we compare the explanatory power of the Alaska and California prices at the longer time horizons. The Alaska price has more significant influence than the California price on the California price and quantity, but has less influence on the Oregon quantity.

The Alaska price, the Alaska quantity and the Washington quantity are exogenous in contemporaneous time, and remain somewhat exogenous at the longer time horizons. Except for the California price, each market's own price (quantity) contributes less to itself at the longer time horizons than in contemporaneous time.

II.5 Summary

Many previous studies associated with the Dungeness crab focused on biology and ecology. Some studies described but did not examine the Dungeness crab price-quantity relationship in specific regions. The objective of this study is to better understand and examine the Dungeness crab price and quantity relations among the four main landing markets including Alaska, Washington, Oregon, and California. Employing the error correction model and DAGs analysis to discover the causal structure among the four states' Dungeness crab prices and quantities, this study makes two important contributions. The first is the application of forecasting tests for the selection of the rank in the ECM model and the DAGs comparisons using the different algorithms to the causal structure of the four crab markets. Second, some of the empirical results are consistent with Dungeness crab ecology and management.

For the model applications, the forecasting tests including RMS error, ln determinant, and the conjecture model based on DAGs provide useful information on selecting the number of cointegrating vectors in the VECM model. The PC-LiNGAM algorithm is a suitable algorithm to deal with partial Gaussian or non-Gaussian data and to determine the undirected edges in the PC algorithm.

For the empirical analysis, the unit root tests show that the four states' Dungeness crab prices are all non-stationary while three among the four states' quantities are stationary possibly due to the crab fishery peaks in a ten-year cycle. The price-quantity causal structure of the West Coast Dungeness crab fishery is represented by the DAGs pattern based on the VECM model. The Alaska quantity is depicted as an island that cannot affect and is not affected by the other prices and quantities. One of the suspected causes is that several stocks have collapsed in some areas of Alaska. The Dungeness crab in the one state cannot move ecologically to the states which are not adjacent to each other, which is consistent with the information on the Dungeness crab movement together with the length of each state's coastline. Besides, California, Oregon, and Washington Dungeness Crab Committees align the management of Dungeness crab. This implies the existence of the causal relationships among the three states' markets. The causal chain from the Alaska price to the California price through the Washington and the Oregon price is generated to cause the two information sinks in the California and the Oregon quantities. The California price blocks the causal chain of the prices to the Oregon and California quantities. The quantity-dependent function exists in California Dungeness crab landing market.

The dynamic interactions among the four Dungeness crab markets are interpreted by the error variance decompositions. Each state's own quantity (price) and the Alaska price jointly explain more than 60% of variation in quantity (price) in contemporaneous time. Moving to the longer time horizons, the Alaska price has more influence on quantities (prices); while the four states' quantities (prices) have less influence on themselves, except for the California price. The causal chain of the four prices contributes more to the Oregon and California quantities at the longer time horizons. The comparison of the explanatory power of the California and the Alaska prices show that the Alaska price has more influence on the California price and quantity at the longer time horizons while the California price has more influence on the Oregon quantity.

This study provides information on the price-quantity causal relationships of the West Coast Dungeness crab fishery. The Dungeness crab management and conservation is a quite important and complicated issue in the West Coast. Before any of the crab management policies and procedures is made, the ecological, environmental, and economic factors should be considered. Berryman (1991) discussed the Dungeness crab ecological chaos can be produced by the economic forces. If the information on the Dungeness crab management policies especially for Washington, Oregon, and California is complete and available, the relationship among prices and quantities and management policies in the Dungeness crab fishery would be an interesting topic in the future research.

CHAPTER III

PREQUENTIAL ANALYSIS AND PRICE AND QUANTITY MANAGEMENT OF COASTAL COMMERCIAL DUNGENESS CRAB

III.1 Introduction

Policy models rely on subjectivity, objectivity, or a mixture of both. If the models are considered from the perspective of applied decision theory, they should generate and assess the probabilities of the system's future path (i.e., probability forecasts). Probability forecasting has been studied under the heading of "prequential analysis" as introduced by Dawid (1984) and is used for many forecasting environments but is not necessary to the definition. More importantly, the use of probability forecasts is advantageous for making decisions because it provides a more complete description of an uncertain future.

Commercial Dungeness crab fishery is of importance on the West Coast including Alaska, Washington, Oregon, and California. The size, sex, and season regulations[19] are tools used to manage the west coast states' crab fisheries. However, any of the Dungeness crab fishery management decisions made by the state governments, crab fishermen, and crabmeat processing and distribution involving the prices and/or yields may have positive/negative impact on the crab biology, fisheries and markets. In order to make more accurate decisions on optimal crab-catching yields, stable crab prices**,** long-

[19] The size, sex, and season regulations are known as the 3-S principle. Only adult male Dungeness crabs over the legal size limit are commercially landed in the fishing seasons every year, and the fishery is closed during the season of year when the crabs are molting and mating.

term profit maximization, the policy/economic models used should be required to test the out-of-sample forecasting rather than the model fit. Besides, comparisons to alternative models may suggest that a single method cannot offer uniformly superior results. One among the methods compared may be superior to another in some variables but may be inferior in the other variables. The economic models we conduct here include two multivariate models (i.e., vector autoregression (VAR) models) and one univariate model (i.e., a random walk model). An empirical comparison between the univariate and multivariate models provides a way to test for the existence of a causal relationship between the variables (e.g., Granger 1980; Covey and Bessler 1992) The purpose of the paper is threefold: (i) to explore prequential relationships among the four western coastal states' Dungeness crab prices and quantities; (ii) to use calibration tests to study the probability forecasts; (iii) to test whether mean forecasts from the univariate and multivariate models fit the actual data well.

Dawid's prequential principle is based on the idea that a main purpose of statistical analysis is to use currently available data to produce sequential probability distributions on future observations. The principle goes beyond agreement with a prior theory and judges a model on its forecasting ability. The assessments of model adequacy (i.e., measures of reliability) are tied to tests of probability calibration (Dawid 1986). The tests are viewed as an idea of the subjective probabilities (Kling and Bessler 1989), which may reflect the Dungeness crab biological conditions and level of management. The probability calibration measures used here contain Pearson's chi-square test and Kolmogorov-Smirnov statistic. The procedure of generating the prequential probabilities requires a forecast of each future year's price and quantity. We apply directed acyclic graphs (DAGs) to test whether links exist among the price and quantity forecasts from these models and the actual data observed for the forecast day. The application of the DAGs is another way to test the accuracy of the forecasting methods.

This paper discusses the prequential analysis of the Dungeness crab markets. As decisions regarding the crab prices and quantities are inherently uncertain and as many if not most decision analyses require expected utility or the entire probability distribution, such methods are primarily of interest. Our contributions include: (i) the comparisons of the univariate and multivariate models provide useful information on the Dungeness crab biology and ecology, which is consistent with the previous studies on the crab. (ii) Some implications from these models will assist state governments, businesses, and fishermen in making more effective and efficient fisheries policies and management decisions. The remainder of the paper is outlined in three sections. First, we discuss the basic concepts of prequential analysis, the methods for testing the probability calibration, and the causal DAG approach. Next, the data used in this analysis are described. The empirical results are then offered and this is followed by a conclusion.

III.2 Methodology

III.2.1 Prequential Analysis

The prequential analysis refers to the process of joining a numerical probability to an uncertain future event. Let $x_t' = (x_{1t}, \dots, x_{mt}), t = 1, \dots, n,$ be realized values of the $(m \times 1)$ vector time series X_t with m defined discrete possible outcomes. Given the realized values $x_t, t = 1, \ldots, n$ at any time n, a set of probability distributions $P_{n,k} = (P_{n+j} | j = 1, \ldots, k)$ for future unknown quantities $x_{n+j}, j = 1, \ldots, k$ must be assigned. A relationship P, which links a choice $P_{n,k}$ with each value of n and with any possible set of outcomes $x_t, t = n + 1, \ldots, n + k$, is termed as a "prequential forecasting system" (PFS) (Dawid 1984). That is, the PFS combines probability forecasting with sequential prediction.

To test the adequacy of prequential probabilities, Dawid's calibration criterion is used. For a well-calibrated PFS, the *ex post* relative frequency of all events whose probability is P^* is actually P^*. For example, a well-calibrated PFS should be sufficiently close to 45-degree line with the relative frequency on the *y*-axis and issued probability on the *x*-axis.

If the random variables $X_{i,t+k}$ are continuous with cumulative distribution functions (CDFs) $F_{i,t+k}$, the random fractiles $U_{i,t+k} = F_{i,t+k}(X_{i,t+k}), t = 1, \ldots, n$, are independent standard uniform ($U[0,1]$) random variables (Dawid 1984). If the $X_{i,t+k}$ are discrete with CDFs $F_{i,t+k}$, then the random fractiles, $U_{i,t+k}$, have the discrete distribution functions of the form $G_{i,t+k}(u_{i,t+k}) = u_{i,t+k}$. In either case, the evaluation of the PFS reduces to a test of hypothesis that the realized sequence $u_{i,t+k} = F_{i,t+k}(x_{i,t+k})$ is from a probability distribution with the CDF $G_{i,t+k}(u_{i,t+k}) = u_{i,t+k}$. Failure to reject the hypothesis means that the PFS is well-calibrated.

The estimated CDF $\hat{G}(U_{i,t+k})$ for $U_{i,t+k}$ is obtained by taking the realized sequence $u_{i,t+k} = F_{i,t+k}(x_{i,t+k}), t = 1, \ldots, n,$ arranging the sequence from low to high order

$u_{i,k}(1), \ldots, u_{i,k}(n)$ and calculating

III.(1) $\hat{G}\left[u_{i,k}(j)\right] = (j/n);\ j = 1, \ldots, n.$

The empirical CDF is referred to as the "calibration function (Bunn 1984) and, for a well-calibrated PFS, should look like a line with slope equal to unity.

III.2.2 Bootstrap Methodology[20]

The 62 observations related to the Dungeness crab landing markets are used to study prequential analysis for model choice (identification). Details on the data will be described later. The models compared in this study are the 8-variable VAR models with 1 lag and 2 lags and the 8-variable random walk model. These models are used to produce forecasts using the chain-rule of forecasting and then to produce probabilistic forecasts using a bootstrap-like procedure as described below.

The general VAR model is

III.(2) $\phi(B)_t X_t = \varepsilon_t$

where $\phi(B)_t$ is the $(m \times m)$ autoregressive parameter matrix (m=8 in this study). The elements of $(B)_t$, individually polynomial functions of the lag operator B, are allowed to change over time throughout the forecast interval and thus are indexed by *t*. X_t is a (8×1) vector; the first four elements are Alaska, Washington, Oregon, and California Dungeness crab quantities and the last four their prices, all realized at the time *t*. ε_t, a (8×1) of innovation, are not correlated over time but may be correlated in cotemporaneous time.

[20] The discussion in this section follows Kling and Bessler (1989).

Following the suggestion given in Fair (1986), two sources of uncertainty are used to produce the probability forecasts--uncertainty in parameter estimates ϕ_t and uncertainty in the one-step-ahead forecasts (call this u_{t+1}, a (8×1) vector).

At each date the elements of $\phi(B)_t$ require the assumption of normality with mean $\hat{\phi}(B)_t$ and covariance $\hat{V}_t = P_t P_t'$. Here the estimated parameter and covariance matrices, $\hat{\phi}(B)_t$ and $\hat{V}_t$, are found from the updating equation III.(2) with Kalman filter at each date *t*. Draws made from the probability distribution used to describe $\phi(B)_t$ model uncertainty in $\phi(B)_t$. A particular draw $\phi(B)_t^*$ is given as

III.(3) $\quad \phi(B)_t^* = \hat{\phi}(B)_t + P_t e$

where e is a (8×1) vector of standard normal draws.

Uncertainty because of the one-step-ahead forecast errors is modelled by drawing (call this draw u_{t+1}^*) from the normality with zero mean vector and the empirical covariance matrix $\hat{\Sigma}_t$ on one-step-ahead forecast error, u_{t+1}. From the historical forecast performance on earlier observations, these latter errors are obtained. Hence an initial period is used to obtain estimates of Σ_t. To achieve this, the sample period is divided into to three intervals. The first 25 observations are used to obtain the OLS estimates of $\phi(B)_t$. The next 10 observations are then used to simulate one-step-ahead forecasts. By recursively forecasting X_{t+1} and updating $\hat{\phi}(B)_t$ over the second interval, a sample of 10 one-step-ahead forecast errors are obtained from which the initial $\hat{\Sigma}_t$ are formed. The last 27 observations are used to model and assess the one-step-ahead probability forecasts.

The one-step-ahead forecast for X_{t+1} is given below

III.(4) $X_{t+1}^{*} = \phi(B)_t^{*} X_t + u_{t+1}^{*}$

Draws on e and u_{t+1} are repeated 1000 times at each date to produce 1000 point forecasts of X_{t+1} at each time t in the third interval. The model is then moved forward one time point (i.e., a year). The Kalman filter is used to obtain the new estimates, $\hat{\phi}(B)_{t+1}$ and $\hat{V}_{t+1}$. Besides, the actual realized X_{t+1} and the mean forecasted X_{t+1} are used to update $\hat{\Sigma}_{t+1}$. The procedure is repeated by each PFS (model) for each of the 27 data points in the third interval.

Following each yearly forecast, the actual outcome (price and quantity realized for the forecast year) is compared to its forecasted distribution to determine the observed fractile for that year.

III.2.3 Tests of Calibration

The hypothesis of a well-calibrated PFS can be examined by testing the observed fractiles from the CDFs from the sequential probability forecasts, $P_{t,k}$. Given the hypothesis, the observed fractiles should follow the uniform distribution on the interval [0, 1] by the probability integral transform. The tests for the uniform distribution are made here using the two goodness-of-fit tests: the Pearson's chi-square test and the Kolmogorov-Smirnov test.

If a sequence of n such forecasts exists, any subinterval of length L (where $0 < L < 1$) will have $n \times L$ observed fractiles under the hypothesis (well calibration) for the Pearson's chi-square test. The test can be applied:

III.(5) $\chi^2 = \sum_{j=1}^{J} [\left(m_j - L_j n\right)^2 / L_j n] \sim X^2(J-1)$.

Here J is the number of non-overlapping subintervals that exhaust the unit interval, m_j is the actual frequency observed in the interval j, and L_j is the length of interval j. The summation is over the J subdivisions on the unit interval, and the number is distributed as the chi-square with J-1 degrees of freedom (Dawid 1984).

The Pearson's chi-square test requires a large number of observations to ensure convergence and provide obscure rules for selecting the number of the subintervals, *J*. An alternative way to test the appropriateness of the uniform distribution, the Kolmogorov-Smirnov test based on the empirical distribution function rather than required binning is used here and is given as

III.(2) $D_n = sup\left[\left|F_n(X) - \hat{F}(X)\right|\right]$

Here n is the total number of data points (where n=27), $\hat{F}(X)$ is fitted CDF, F_n is the empirical distribution function equal to $\frac{N_x}{n}$, and N_x is the number of X_i that are less than X. The measure of the vertical difference between $F_n(X)$ and $\hat{F}(X)$ belongs to the supremum class of empirical distribution function statistics. The Kolmogorov-Smirnov test takes advantage of distribution free assumption (i.e., no assumption about the distribution of the data) but focuses on the middle of distribution and does not detect tail discrepancies very well.

III.2.4 Directed Acyclic Graphs (DAGs)

Using the bootstrap, the prequential analysis yields 1000 point forecasts of X_{t+1} at each time t in the third interval. In order to evaluate the forecasting ability, the mean forecasted X_{t+1} at each time t is calculated to compare with the actual outcome (price and quantity observed for the forecast time). More clearly, based on the concept of Bessler and Wang's 2012 conjecture model[21], we examine the hypothetical information links among the mean forecasts from the models and the actual realization of the variable of interest applying directed acyclic graphs (DAGs).

DAGs consist of nodes, edges, and arrowheads but no self-loops and no directed cycles to summarize the causal relationships among a set of variables (Pearl 2000). Peter and Clark (PC) algorithm is a way to generate the DAGs and to test whether the causal flows exist. The PC algorithm starts by considering a completely connected undirected graph G on the set of variables to be determined. Edges between variables are removed sequentially based on zero unconditional correlation and conditional correlation at some pre-specified significance level of normal distribution. *The conditioning variable(s) on the removed lines between two variables is called the sepset, as defined in Bessler and Akleman (1998), of the variables whose line has been removed (for vanishing zero-order conditioning information the sepset is an empty set).* For an example of triples A−B−C, A−B−C can be directed as an inverted fork A→C←B if C is not in the sepset of A and B. If the correlation between A and B conditional on C is zero, the underlying model may have been a causal chain A→C→B or a fork chain A←C→B. Then, the edge between A, B and C would not be directed so that the undirected edges A−C−B would be left under the PC algorithm.

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[21] The conjecture model is defined in Bessler and Wang (2012): "Scientists implicitly seek a model, theory, or explanation whose forecasts d-separate predictions that are derived from inferior models, theories, or explanations and Actual realizations of the world."

At small data size, the PC algorithm may erroneously add or remove edges and direct edges at the traditional 0.05 and 0.1 significance level. Monte Carlo studies with small sizes has been discussed in Spirtes, Glymour, and Scheines (2000, pp. 116): "In order for the model to converge to the correct decisions with probability 1, the significance level used in making decisions should decrease as the sample sizes increase, and the use of higher significance levels (e.g., 0.2 at the sample sizes less than 100, and 0.1 at sample sizes between 100 and 300) may improve performance at small sizes." The PC algorithm will be applied at the 0.2 significance level here because the data size used here is less than 100.

III.3 Crab Data

The data set used here has 62 annual observations from the four western coastal states' Dungeness crab landing markets from 1951 to 2012. There are 8 variables consisting of the commercial quantities of the crab landing in Alaska, Washington, Oregon and California in pounds of round (live) weight (lbs) and their landing prices (US cent/lb). The price and quantity data obtained from the NOAA's National Marine Fisheries Service (NOAA_Fisheries) are used to study prequential analysis for model selection. The models we compare include two multivariate models (the 8-variable VAR models with 1 lag and 2 lags) and one univariate model (the 8-variable random walk model). The data points from 1951 to 1975 on each price and quantity series are used to identify and fit these models. These models are used to produce one-step-ahead forecasts over data points in the period 1976-1985. The kalman filter (carried out in RATS (Doan) software) is used to generate recursive forecasting and coefficient updating. The period 1986-2012 is used to judge the reliability of these models using probability calibration measures. The same period is also used to examine whether the mean forecasts from these models fit the actual data well using the PC algorithm. The PC algorithm is available under the Tetrad project at Carnegie Mellon University. The "knowledge" component of the PC algorithm is used to prevent the actual from affecting the forecast (the future cannot affect the past).

III.4 Empirical Results

Table III.1 summarizes root mean square error (RMSE), the Pearson's chi-square statistic, and the Kolmogorov-Smirnov statistic for each PFS over the time period 1986-2012. At each date, the forecasts are for one step ahead, and then the observed data point and its forecasted distribution are compared to determine the observed fractile for that date. By the probability integral transform the observed fractiles should be uniformly distributed on (0, 1). The RMSE[22] is used here for measuring the squared differences between the observed fractiles and the standard uniform distribution. The results for these price and quantity series in these three models are shown in the second column of table III.1. The larger RMSE values occur in the Alaska quantity in the 1-lag VAR

[22] The root mean square error (RMSE) is a frequently used measure of the deviation of the values predicted by a model or an estimator ($Y_{model,i}$) from the real world observations ($Y_{obs,i}$):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{model,i} - Y_{obs,i})^2}$$

The smaller RMSE values indicate greater predictive ability or better model fits.

model (the RMSE value of 0.10), the Alaska quantity and California quantity in the 2-lag VAR model (0.15), and the Washington quantity in the random walk model (0.13). The RMSE value is negatively correlated with how well the series is calibrated.

To evaluate the performance of these models, the average RMSE of the 8 price and quantity series is calculated for each model. The 1-lag VAR model perform best with an average RMSE of 0.06, followed by the random walk model with 0.08 and the 2-lag VAR model with 0.09. Although the RMSE enables us to compare and rank these models, it provides no absolute criterion for a good value and no way to examine the null hypothesis of a well calibrated PFS.

The null hypothesis (well calibration) can be examined by the Kolmogorov-Smirnov test and the Pearson's chi-square test; the main difference between the two tests is that they can be applicable to un-binned and binned data respectively. Binning is a process of placing the observed fractiles into N non-overlapping and exhaustive classes. The Pearson's chi-square test is used to test whether the number of fractiles realized in each class is contrasted to the number expected. The value of the chi-square test is sensitive to how the data is binned, and the same data with different bin widths may cause the discrepancy (rejecting the hypothesis for the specific bins but not for the other bins). Such discrepancy exists in the Washington quantity[23] and Alaska price of the random walk and the Alaska quantity of the 1-lag VAR (shown in table III.1), but there are no clear criteria for selecting the optimal number of bins.

[23] For the Washington quantity in the random walk, at the 5% significance level, the hypothesis (well calibration) is rejected in the Pearson's chi-square test with 4 bins but not rejected with 5, 10, and 20 bins.

Table III.1. RMSE and Goodness of Fit Statistics on VAR and Random Walk on the Horizon of 1 Step Ahead

Forecasted Variables	RMSE	Pearson's Chi-Square Statistic[a] Class 4	5	10	20	Kolmogorov–Smirnov Test
VAR-1 lag						
Alaska Quantity	0.10	13.44*	8.00	14.85	38.93*	0.20
Washington Quantity	0.04	1.30	3.19	14.11	24.11	0.13
Oregon Quantity	0.04	1.00	1.70	6.70	9.30	0.15
California Quantity	0.09	6.93	5.41	11.15	27.07	0.23
Alaska Price	0.06	3.07	3.93	9.67	15.22	0.16
Washington Price	0.04	0.41	0.96	11.15	28.56	0.14
Oregon Price	0.07	2.48	1.33	3.74	21.15	0.21
California Price	0.05	2.78	1.70	3.00	13.74	0.16
VAR-2 lags						
Alaska Quantity	0.15	20.56*	20.59*	28.19*	31.52*	0.25*
Washington Quantity	0.04	1.30	1.33	3.00	18.19	0.15
Oregon Quantity	0.12	6.33	8.00	9.52	18.19	0.25*
California Quantity	0.15	15.52*	15.41*	22.26*	33.00*	0.31*
Alaska Price	0.06	3.07	5.41	13.37	15.22	0.13
Washington Price	0.07	5.15	6.15	15.74	18.19	0.17
Oregon Price	0.06	3.67	2.81	6.70	12.26	0.12
California Price	0.04	0.70	0.22	5.96	16.70	0.11
Random Walk						
Alaska Quantity	0.09	3.07	5.41	7.44	22.63	0.18
Washington Quantity	0.13	8.11*	7.63	11.15	22.63	0.28*
Oregon Quantity	0.05	1.37	1.70	8.19	13.74	0.15
California Quantity	0.07	1.00	3.56	6.70	12.26	0.18
Alaska Price	0.08	1.89	6.15	11.89	38.93*	0.22
Washington Price	0.07	4.56	3.19	12.63	19.67	0.17
Oregon Price	0.05	0.70	0.96	5.81	22.63	0.15
California Price	0.08	2.78	6.15	16.33	22.63	0.22

[a] The classes studied includes 4, 5, 10, and 20 and their 5% critical values are 7.81, 9.49, 16.92, and 30.14 respectively.

[b] For the Kolmogorov–Smirnov test, the hypothesis regarding the uniform distribution is rejected if the test statistic is greater than the 5% critical value of 0.25.

Note: Rejection at significance level of 5% or less is indicated by *.

To avoid the biased results from the bin size selection, we consider the four different bin widths in the Pearson's chi-square test and an alternative test, the "un-binned" Kolmogorov-Smirnov statistic. The number of bins selected here includes 4, 5, 10, and 20; their 5% critical values of the chi-square test are 7.81, 9.49, 16.92, and 30.14 respectively. For the Kolmogorov-Smirnov test, the hypothesis regarding the uniform distribution is rejected if the test statistic is greater than the 5% critical value of 0.25.

The results of these binned and un-binned goodness-of-fit tests are shown in the last five columns of table III.1. It is clear that the 2-lag VAR is outperformed by the 1-lag VAR and the random walk for a one-step-ahead forecast. In the 2-lag VAR, the Pearson's chi-square tests with a total of 4, 5, 10, and 20 bins as well as the Kolmogorov-Smirnov test reject the forecasts from the Alaska and California quantities as being well-calibrated. Such series whose hypothesis is rejected by all the tests is not found in the 1-lag VAR and the random walk. It is only less well-calibrated for the Alaska quantity of the 1-lag VAR in the chi-square test with 4 and 20 bins. For the random walk, the Alaska price is viewed as miscalibrated in the chi-square test with 20 bins and the Washington quantity in the test with 4 bins together with the Kolmogorov-Smirnov test.

Most series in the l-lag VAR and the random walk do not significantly depart from well-calibration. The 1-lag VAR possesses more well-calibrated price series than the random walk by one, and each of them has 3 well-calibrated quantity series respectively. In order to further evaluate whether the random walk or the 1-lag VAR performs better and under what circumstances, the values of the test statistic of the two goodness-of-fit tests (lower value is better) and the calibration plots on probability forecasts of the all series should also be considered. Besides, additional information would be provided by application of DAGs to testing the forecast adequacy of the 1-lag VAR and the random walk models.

Calibration functions from the 1-lag VAR and the random walk are shown in Figure III.1. In each plot, the horizontal axis is the issued fractile, whereas the vertical axis is the relative frequency. The fractile-relative frequency plot of a well-calibrated model should be the 45-degree line. For the Washington quantity and Alaska price, the random walk model deviates more from the 45-degree lines and shows poorer calibration than the 1-lag VAR; but it is opposite to the Alaska quantity. The above descriptions of these three series are quite consistent with the results of the two goodness-of-fit tests. The remaining five series are all well-calibrated in the two goodness-of-fit tests but may perform better in one model than the other model shown in the calibration plots. The California quantity and the Oregon price in the random walk are much closer to the 45-degree line; while the Washington price, the Oregon quantity, and the California price in the 1-lag VAR are much closer to the 45-degree line.

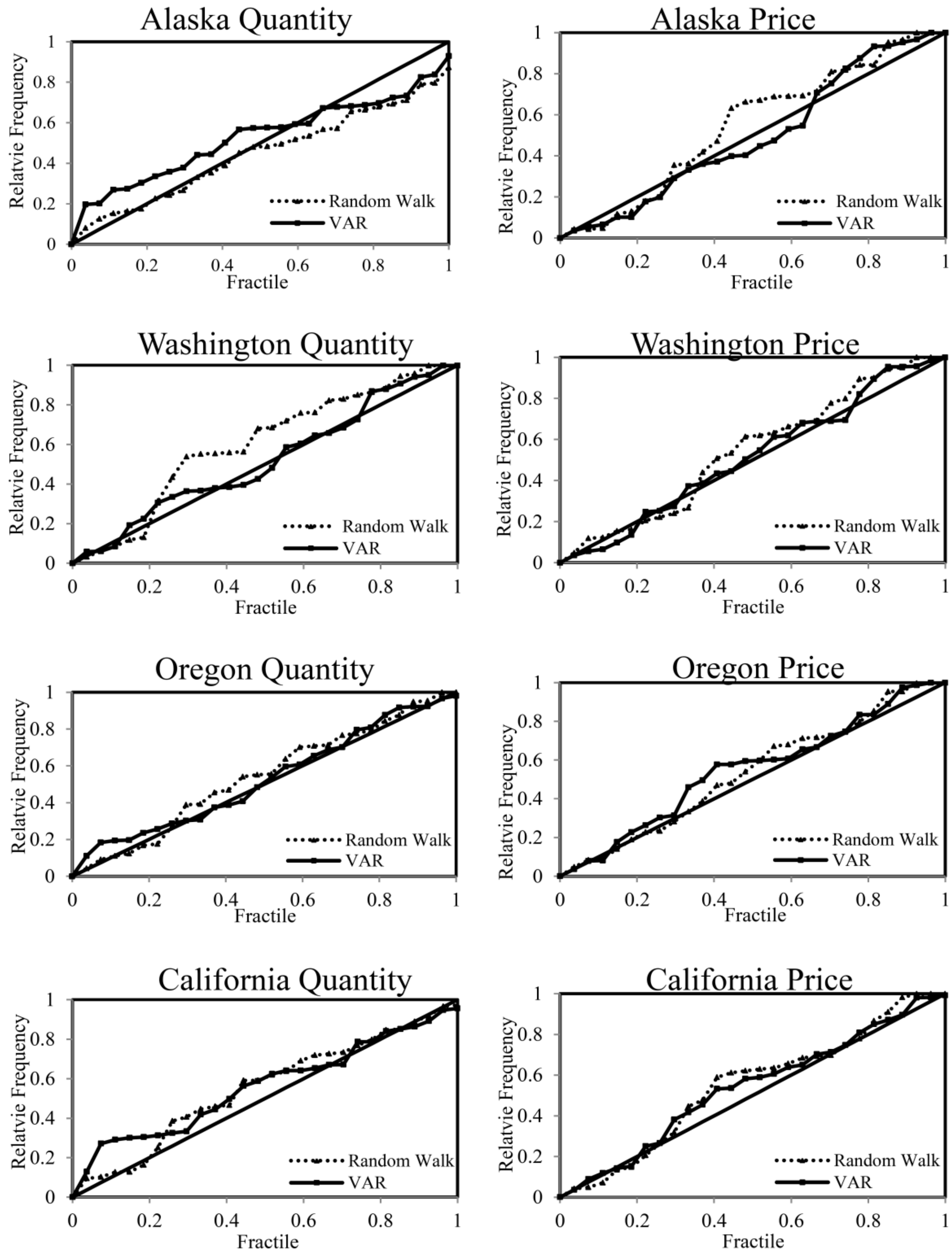

Figure III.1. Calibration Functions of the Four State's Price and Quantity Series, 1986-2012, by 1-lag VAR and Random Walk

Figure III.2 illustrates the causal relationships[24] among the forecasts from the 1-lag VAR and the random walk and the actual data found with the PC algorithm. Here, we do not know the direction of arrows between the random walk forecast and the 1-lag VAR forecast: either the 1-lag VAR ← the random walk or the l-lag VAR → the random walk. At one-step-ahead the random walk sits as a blocking node separating information flow from the 1-lag VAR to the actual Alaska quantities, Washington quantities and Oregon prices; whereas the 1-lag VAR blocks information from the random walk to the actual Alaska prices and California prices and quantities. The causal structures of the Alaska price and quantity cohere well with the results reported in the probability calibration measures. Here, there is a discrepancy with the Washington quantity: the series in the random walk is not well-calibrated but its forecasts express the actual well.

[24] The forecasts of the 2-lag VAR model are added to the existing causal structures. The results show that forecasts from the 2-lag VAR do not cause the actual data. Similarly, we do not know the direction of arrow between the random walk, the 1-lag VAR and the 2-lag VAR (that is, the random walk − the 1-lag VAR − the 2-lag VAR). For almost all series, the new patterns associated with the three models (adding of the 2-lag VAR) are identical (similar) to the original patterns of the two models. The only different pattern is that the 1-lag VAR, the 2-lag VAR and the random walk are not connected to the actual Alaska prices.

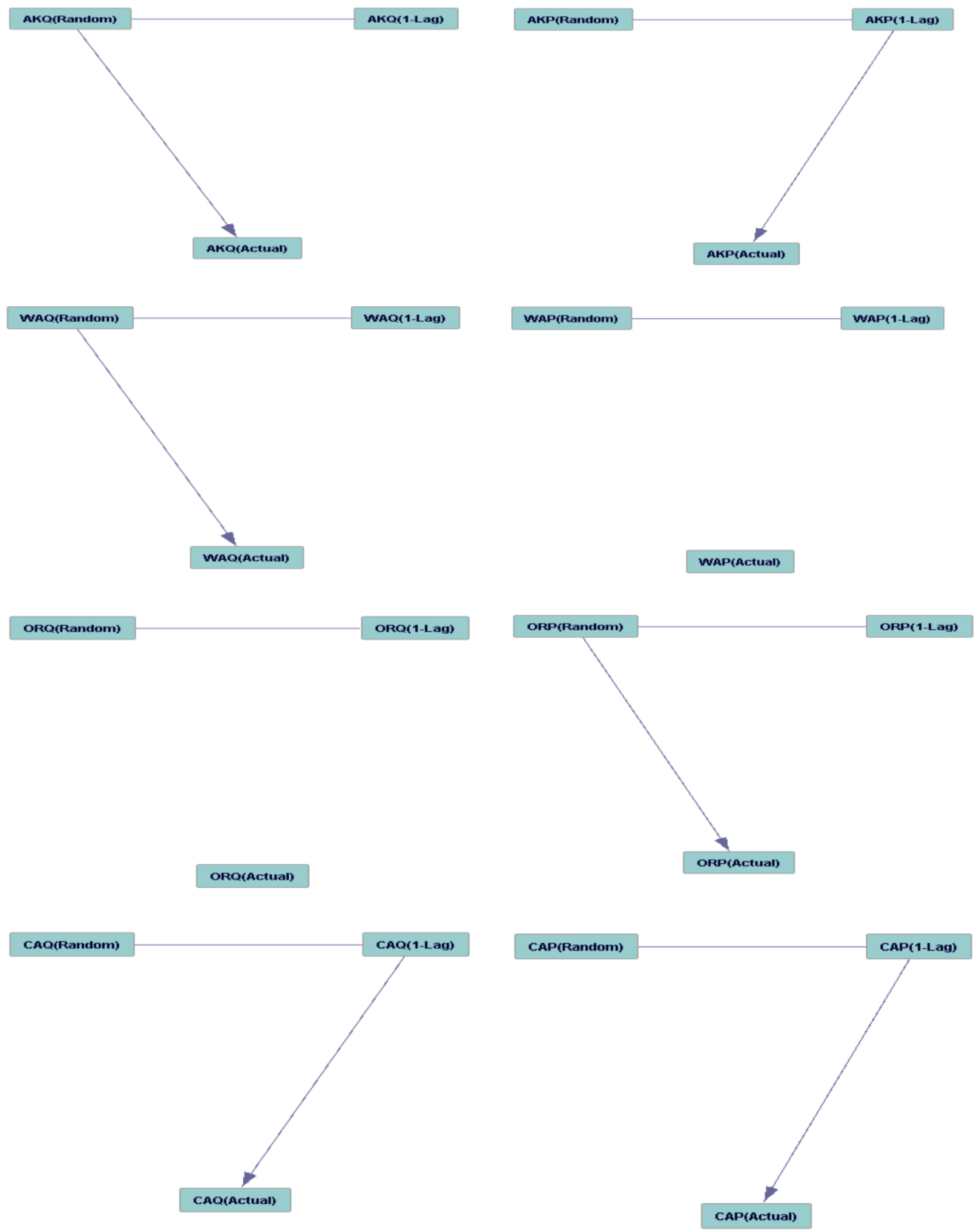

Figure III.2. Patterns from PC Algorithm on One-Step-Ahead Forecasts from Random Walk (Random) and 1-Lag VAR (1-Lag) and Actual, 1986-2012.

We compare the performance of the random walk and the 1-lag VAR using the following three principles. One model (this model) may be superior to the other model for each series if (i) only this model offers prequentially well-calibrated forecasts; (ii) almost all the test statistics for this model are much lower when the two models are all well calibrated; (iii) the forecasts from the other model is blocked by this model's forecasts in their path to the actual. Table III.2 gives the performance measures using zero-one indicator for each series. A zero (0) indicates the random walk forecast outperforms the 1-lag VAR for that measure on that particular series. A one (1) indicates that the 1-lag VAR outperforms the random walk.

Table III.2. Indicators of Dominance: the 1-lag VAR (1) Versus the Random Walk (0) for the Goodness-of-Fit Tests and the Causal Graphs

Variables	Pearson's Chi-Square Statistic	Kolmogorov–Smirnov Test	Causal Graphs	**Summary**
Alaska Quantity (AKQ)	0	0	0	**0**
Washington Quantity (WAQ)	1	1	0	**1**
Oregon Quantity (ORQ)	1	0	-	**-**
California Quantity (CAQ)	0	0	1	**0**
Summary	**-**	**0**	**0**	**0**
Alaska Price (AKP)	1	1	1	**1**
Washington Price (WAP)	1	1	-	**1**
Oregon Price (ORP)	-	0	0	**0**
California Price (CAP)	1	1	1	**1**
Summary	**1**	**1**	**1**	**1**

Notes: A zero (0) indicates the random walk outperforms the 1-lag VAR on the particular measure for one-step-ahead forecasts. A one (1) indicates that the 1-lag VAR outperforms the random walk on the measure. A '-' indicates that the two models have the same score (the models tied with regard to that measure).

For the four states' Dungeness crab quantities, the random walk is compared to the 1-lag VAR from three angles: summaries of the four quantity series, summaries of the three measures, and all the 12 cases. First, as given in the sixth row of table III.2, there is no clear dominance of the random walk over the 1-lag VAR using the Pearson's chi-square test; the random walk outperform the 1-lag VAR on the Kolmogorov-Smirnov test and the causal graphs. Second, with regard to the results of the three measures, the random walk is superior for Alaska and California quantities but interior for the Washington quantity (see the fifth column of table III.2) Third, of the 12 cases studied, the random walk dominates in 6 cases and is dominated by the 1-lag VAR in 4. According to the above results, it seems that random walk does slightly better than the 1-lag VAR for the four states' crab quantity (production) forecasts. There might be some implications of the random walk for the Dungeness crab production. The random walk formula defines that the prediction of the one states' future crab production is its current production and neither its current price nor the other states' prices and quantities matter. Clearly, there is no direct causal links among the four states' production, which is consistent with the crab biology and ecology knowledge that many adult Dungeness crabs move very little and stay in the same area for their whole lives (Johnson et al. 1986; Stone and O'Clair 2001). Besides, the random walk theory tells that these quantity series themselves are not random but the changes from one period to the next are random. The Dungeness crab production cannot be predicted well just by its past catch record reports but by many factors such as the crab population cycles and the causes of the cycles. For example, the Dungeness crab production records along the West Coast vary in a cyclic pattern (Botsford et al. 1998). The crab abundance peaks in around 10-year cycles (Dewees et al. 2004). The cycles is primarily due to (i) predator-prey systems with both salmon and human as predictors, (ii) exogenous environmental forces such as ocean temperature, surface winds, alongshore flow, and sea level, (iii) density-dependent (biological) mechanisms containing density-dependent fecundity**,** an egg-predator worm and cannibalism (Botsford et al. 1998). All of the underlying causes of the crab production fluctuations should be considered to provide a more accurate picture of the crab stocks and then to design more accurate fisheries management systems involving when, where, how, and how much the fishermen are allowed to catch. Due to dramatic production fluctuations and a sudden decrease in the crab harvest without warning, buying yield insurances, a risk management tool, may protect the fishermen against yield losses. To prevent future crab shortage, the crab distributers may make quantity agreements with the fishermen to maintain a certain level of quantity and quality of production or preserve the current Dungeness crab (frozen and canned crabmeat).

For each quantity series, the forecast performances of the two models on the two goodness-fit tests and the causal analysis are discussed below. From the second row of table III.2, the random walk forecasts of the Alaska quantity dominate the forecasts from the 1-lag VAR on all the three measures, which suggests that the current Alaska quantity does not significantly depend on its previous price and the other states' previous prices and quantities. So far, the stocks have collapsed in some regions Alaska, possibly due to overfishing, sea otter predation, and adverse climatic changes (Woodby et al. 2005). The current price policies may not improve the allocation of the Alaska Dungeness crab resource in the future**.** For California, Oregon, and Washington quantity series, each model (random walk and 1-lags VAR) performs better on the particular measures but do not on the other measures. To our knowledge, California, Oregon, and Washington Dungeness Crab Committees[25] align the management of Dungeness crab such as to determine the commercial fishing season dates and the total harvest. We conjecture that despite the random and possibly dramatic harvest fluctuations, this year's government interventions such as the four states' crab harvest and price policies may have some effects on the three states' crab production for next year.

For the four states' Dungeness crab prices, the 1-lag VAR outperforms the random walk from the three angles (have been used for the four crab quantities). The 1-lag VAR illustrates that the one state's future crab prices will be affected by the four states' current crab prices and quantities. This model will not only help the state governments to make effective and efficient price policies but also help the seller and buyer in wholesale fish market (organized as a Dutch auction[26]) to find the reasonable crab prices. For each state's Dungeness crab price, the 1-lag VAR is superior to the random walk, except for the Oregon price. Although the two goodness-of-fit tests fail to reject the forecasts from the Oregon price as being well-calibrated (see table III.1), the random walk has lower value of Kolmogorov-Smirnov test statistic, and the forecasts from the random walk fit

[25] The tri-state Dungeness crab committee was formed in 1998, and the details are available at https://www.govtrack.us/congress/bills/105/s1726/text

[26] A Dutch auction is a descending-price auction where the auctioneer begins with a high asking price which is gradually lowered until there is a bidder is willing to accept the amount being asked.

the actual Oregon prices well (see figure III.2). Hence, the Oregon price fluctuations are possibly random. The Oregon Dungeness crab prices have been summarized in Demory (1990): “The price of crab to fishermen depends upon several factors. Since about 70% of Oregon crab is marketed in California, the California pricing mechanism controls the Oregon and Washington price as well. The previous year's fishery also affects the price. High volume one year and perhaps a soft market because of the volume available, will prompt a low price for the opening of the following season. Poor crab condition will also depress the price.” To provide significant Oregon crab price forecasts, not only the above factors but also such factors as changes in consumer preference and changes in the crab fishery circumstances should be considered.

III.5 Conclusion

This paper applies prequential analysis to one univariate model (a random walk) and two multivariate models (a 1-lag VAR and a 2-lag VAR) of the West Coast Commercial Dungeness crab landing markets and give suggestions on the Dungeness crab fishery management. ‘Binned’ Pearson chi-square test and ‘un-binned’ Kolmogorov-Smirnov test and causal graphs among the model forecasts and the actual data are considered. Eight variables used in this paper consist of Alaska, Washington, Oregon, and California landing quantities and their prices. Both probability forecasts and mean forecasts of one model are compared to these forecasts of the other models. This paper finds that the 2-lag VAR is less well calibrated than the 1-lag VAR and the random walk. Most of the series in the l-lag VAR and the random walk are well-calibrated so that additional information including the two test statistics and causal directed acyclic graphs (DAGs) are used to compare the two models.

For the four states' crab production, the random walk may provide slightly better forecasts than the 1-lag and has two implications. First, no direct relations among the four states' crab production implies that many adult Dungeness crabs live their whole lives in the same location. Second, the production fluctuations from one period to the next are random and may be dramatic. For the state governments, all the potential causes of the fluctuations should be considered to design more accurate fisheries management systems to maintain the crab stock and productivity. The fishermen may buy yield insurances against the harvest fluctuations. The crab distributers make quantity contracts with the crab suppliers or/and preserve the Dungeness crab against the crab shortage. For each quantity series, whether the forecasts from the random walk are superior or inferior to the forecasts from the 1-lag VAR, are tested. The random walk of the Alaska quantity suggests that the previous price controls might not significantly improve the current collapse of the Alaska Dungeness crab fishery. For the California, Oregon, and Washington quantities, the random walk and 1-lag VAR outperform each other on some but not all of the measures. We conjecture that the price and harvest policies made by the tri-state Dungeness crab committee presently recently may have some effects against the dramatic fluctuations of the crab production for the next year.

The 1-lag VAR is more appropriate to analyze the four states' Dungeness crab prices. This model may help to predict the future crab price, to make more accurate price policies of the crab and to find the reasonable crab prices in fish auctions. For each state's crab price, the 1-lag VAR dominate the random walk, except for the Oregon price. All the four states' current crab prices and quantities are important factors in predicting Alaska, Washington, and California crab price for next year. However, to significantly predict the Oregon crab prices, we should consider not only the factors discussed in Demory (1990) (e.g., expectation from fishermen and quality of crab) but also such factors as changes in consumer preference and changes in the crab fishery circumstances.

This paper studies the dynamic linear models, the nonlinear dynamical models could be an alternative model for the future studies. Normal draws is used in this paper to calculate the probability forecasts. Further research on the prequential analysis could consider non-normal draw in some specific situation. Additional research should include measure of sorting such as Brier scores and their partitions.

CHAPTER IV

AN ANALYSIS OF DUNGENESS CRAB YIELD INSURANCE FOR THE WEST COAST

IV.1 Introduction

Dungeness crab, formerly Cancer magister, is one of the most popular seafood menu items on the West Coast. During the period from 2003 to 2012, it was among the three most valuable West Coast commercial crabs[27] and has higher production volumes and values than the other crabs in nine of these ten years.

The Dungeness crab is harvested from Point Conception in California to the Pribilof Islands in Alaska. Under the 3-S (sex, size, and season) principle, only sexually mature male crabs larger than the minimum legal size can be landed in the fishing seasons. The 3-S principle may not be sufficient to maintain stock productivity at high harvest pressure (Bishop, Siddeek, and Rumble 2007). For example, the crab stock has collapsed in some areas of Alaska and the possible reasons for this collapse include overfishing, sea otter predation, and adverse climatic changes (Woodby et al. 2005).

Each western costal state's commercial Dungeness crab fishery has exhibited periods of high- and low-volume production. Especially, between northern California and Washington, the crab catch records vary in a cyclical pattern (Botsford et al. 1998). The crab abundance peaks in approximate 10-year cycles (Dewees et al. 2004).

[27] The National Oceanic and Atmospheric Administration statistics show that Dungeness crab, snow crab, and king crab are the three most valuable commercial crabs on the West Coast over the time period 2003-2012.

According to the above information, the Dungeness crab fishermen may face two major risks: dramatic fluctuations in the crab catches and sudden decreases in the crab harvest without warning. It is quite important for the fishermen to manage and reduce risk of the lower crab harvests.

Traditional agricultural producers (e.g., farmers and ranchers) can purchase crop-yield insurance to protect themselves against the unpreventable loss of their crops due to natural disasters. Looking at the yield distributions is an important step to describe crop yields and estimate the fair insurance premium. Much of the agricultural insurance literature focused on crop yield distributions or/and insurance valuations such as Day (1965), Gallagher (1986 and 1987), Moss and Shonkwiler (1993), Ker and Goodwin (2000), and Sherrick et al. (2004). To our knowledge, the Dungeness crab fishermen do not have the option to buy a crab-yield insurance policy. No empirical research has estimated probability distributions for the Dungeness crab yields nor explored the crab insurance premiums.

Detrended historical crop yields are frequently used for obtaining stationary time series of residuals to assess the crop yield risk and insurance premiums. In this paper, a vector error correction model (VECM) will be used to detrend the Dungeness crab yield and price data in Alaska, Washington, Oregon, and California. The best fitting distribution for the state-level crab yield and price residual data will be selected using three goodness-of-fit tests: Chi-square, and Kolmogorov-Smirnov, and Anderson-Darling. Validation of the VECM model along with the selected probability densities will be performed. The main purpose of the paper is to estimate the Dungeness crab yield insurance premiums and the probabilities of paying indemnities. The information may help USDA-RMB to decide whether or not the insurances should be provided to these crab fishermen. Our contributions are: (i) Each state's Dungeness crab yield distribution and its crab price distribution are evaluated. (ii) The fair premium rates of the four states' Dungeness crab yield insurance are estimated using the estimated probability distributions of the crab prices and yields. (iii) The probabilities that the indemnities are paid to the fishermen are calculated.

The remainder of the paper is organized in four sections. First, the methodology is presented which includes the concepts of the VECM model, the parametric probability distributions, and the goodness-of-fit tests, and the method for calculating the insurance premiums for the Dungeness crab. Second, the data is presented. Third, the empirical results are offered and finally a summary concludes the paper.

IV.2 Methodology

IV.2.1 Vector Error Correction Model (VECM)

Empirical economics suggests that some types of relationships exist among the four western coastal states' Dungeness crab landing prices and yields. Hence, a multivariate model might be more appropriate than a univariate model to detrend the four states' Dungeness crab prices and yields. When some non-stationary and cointegrated variables exist in the evaluated data, the error correction framework is seen as a useful tool for detrending. The VECM model (Engle and Granger 1987; Hansen and Juselius 1995; Jonathan 2006; Juselius 2006) is written as:

IV.(1) $\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \mu + e_t \ \ (t = 1, \ldots, T)$

where Δ is the difference operator ($\Delta Y_t = Y_t - Y_{t-1}$), Y_t is a (8×1) vector of the four-state prices and yields measured at time t, Π is a (8×8) matrix of coefficients relating lagged level of series to current changes in series, Γ_i is a (8×8) matrix of coefficients relating series changes at lagged i- period to current changes in series, μ is a (8×1) vector of constant, and e_t is a (8×1) vector of independent, identically distributed (i.i.d) innovations (i.e., residuals).

The Π can be represented as $\alpha\beta'$, where α and β are $(8 \times r)$ matrices of full rank, and r is a positive number less than or equal to the number of variables. The r is defined as the rank of Π and is determined by Johansen's trace test (Juselius 2006). The residuals of the VECM model are retained as detrended data to assess the probability distributions of the Dungeness crab prices and yields in each western coastal state. This information is used to estimate the state-level premium rates given in cents per pound for the crab yield insurance.

IV.2.2 Parametric Probability Distributions

The probability destiny functions (PDFs) of the detrended prices and yields can be estimated by either non-parametric or parametric modeling approaches. The difference between these two approaches is that the parametric distributions are not distribution-free and makes assumptions about the properties (i.e., parameters) of the evaluated variables. When the sample sizes are small, the parametric approaches dominate the nonparametric ones (Upadhyay and Smith 2005). In this paper, several parametric distributions are selected as candidate distributions including logistic, lognormal, log-

logistic, normal, Weibull, inverse Gaussian, and Gamma distributions. Alternative parameterizations of crop yield distributions have been examined in past studies: lognormal (e,g, Day 1965), Gamma (e.g., Pope and Ziemer 1984;Gallagher 1987), normal (e.g., Just and Weninger 1999), logistic (e.g., Sherrick et al. 2004), Weibull (e.g., Sherrick et al. 2004; Chen and Miranda 2004), log-logistic (e.g., Wilson, Gustafson, and Dahl 2009) and inverse Gaussian (Lanoue et al. 2010). Few researchers focused on modeling the crop price distributions (e.g., Tew and Reid 1988). This study measures how well not only the crab yields but also its prices fit the above-mentioned parametric distributions. Because each of these distributions has two estimated parameters, the resulting differences do not relate mainly to differences in the number of estimated parameters but to the underlying properties of each distribution. The maximum-likelihood method is used to estimate the parameters of each of the seven probability distributions of the state-level detrended prices and yields.

IV.2.3 Goodness-of-Fit Tests

The goodness-of-fit tests assess the adequacy of the seven selected parametric probability distributions and rank them for describing the four state-level crab price and yield distributions. Here, Chi-square, Kolmogorov-Smirnov (K-S), and Anderson-Darling (A-D) goodness-of fit tests are used.

The Chi-square test, the best known goodness-of-fit test, can be used with the data made up of both continuous and discrete variables. The data are put into m non-overlapping bins, and the test statistic is defined as:

IV.(2) $\chi^2 = \sum_{i=1}^{m} \frac{(O_i - E_i)^2}{E_i} \sim \chi^2(m-1)$

Where O_i is the observed frequency in the i^{th} bin, and E_i is the frequency expected in the i^{th} bin if the null hypothesis is true. The summation is over the m bins of data and the number is distributed as the Chi-square with $m-1$ degrees of freedom.

There are two weakness of using the Chi-square test for goodness-of-fit testing. First, the test requires the sample size large enough to ensure convergence. Second, the value of the Chi-square test statistic is sensitive to how the data is binned. There is no optimal rule for choosing the number and location of the bins. Therefore, both the K-S and A-D tests based on the empirical distribution function but not on the bins are also used to examine and rank the candidate probability distributions fitted to the detrended data.

The K-S test can be used with continuous sample data and is defined as:

IV.(3) $D_n = sup_x\left[\left|F_n(X) - \hat{F}(X)\right|\right]$

Where n is the total number of data points, $\hat{F}(X)$ is the fitted cumulative distribution function (CDF), F_n is the empirical distribution function (EDF) that equals $\frac{1}{n}\sum_{i=1}^{n} I_{X_i \leq x}$, where $I_{X_i \leq x}$ is the indicator function equal to 1 if X_i is less than x and equal to 0 otherwise. The K-S test measures the supremum (sup) difference between $F_n(X)$ and $\hat{F}(X)$. However, the test focuses on the middle of distribution and detects tail discrepancies poorly.

The A-D test modifies the K-S test to emphasize the differences between the tails of the fitted distribution and the evaluated data. The function form of the A-D test is given as:

IV.(4) $A_n^2 = n \int_{-\infty}^{+\infty} \left[F_n(x) - \hat{F}(x)\right]^2 \psi(x)\hat{f}(x)dx$

where $\hat{F}(x)$ is the hypothesized cumulative distribution, $\hat{f}(x)$ is the hypothesized density function, $\psi(x)$ is the weight function equal to $1/\{\hat{F}(x)[1 - \hat{F}(x)]\}$. The A-D test allows a more sensitive test but the critical values for each distribution need to be calculated.

IV.2.3 Premium Rates of Crab-Yield Insurance

When crop-yield insurance is designed, the probability distributions of the crop yields are viewed as a signal of risk exposure and an input used to estimate the crop insurance premiums (e.g., Ker and Goodwin 2000; Sherrick et al. 2004; Lanoue et al. 2010). The three goodness-of-fit measures are used to select the best fitting probability distribution not only for each state's detrended Dungeness crab yield data but also for its detrended price data. Then, the state-level crab insurance premiums per pound (in cents) are estimated using these probability distributions. The details are given:

The realized revenue falling below a fisherman's selected guaranteed level equals the revenue losses suffered by the fisherman to compensate for the losses. When the crab-yield insurance exists, an indemnity payment is made to the fisherman. The total indemnity (G) is calculated as the insured revenue (IR) minus the realized revenue $(\widetilde{RR})$ and is mathematically given as:

IV.(5) $G = \max\left(0, IR - \widetilde{RR}\right)$

$$= \max\left(0, \left(h * \bar{Q}_t * \hat{P}_{t+1}\right) - \left(\bar{Q}_t + e_{Qt}\right) * \left(\hat{P}_{t+1} + e_{Pt}\right)\right)$$

Where h is the level of yield coverage chosen, $\bar{Q}_t$ is the average Dungeness crab fishing yield over the last ten years (from 2003 to 2012), $\hat{P}_{t+1}$ is the expected crab price in the next period (in 2013) forecasted by the VECM model, e_{Qt} is the detrended yields best described by a specific two-parameter probability distribution density, e_{Pt} is the detrended prices following a probability distribution function. The insured revenue consists of the yield coverage level, the average crab yield of the last ten years, and the expected crab price for the next period; while the realized revenue equals the 10-year average yield plus the simulated detrended yield times the next period's expected price plus the simulated detrended price.

In each state, under the assumption of 50%, 60%, 70% and 80% yield coverage levels, the indemnity payment shown in equation IV.(5) is simulated 500 times. The probability that the simulated indemnity values are greater than zero (i.e. the realized revenue less than the insured revenue) is calculated as the probability of the indemnity being paid to the crab fishermen; while the mean value of the 500 simulations divided by the 10-year average yield is calculated as the Dungeness crab insurance premium rate per pound.

In this study, RATS program and @risk software (Palisade 2010) are conducted to set up the VECM model and find the parametric probability distributions best suiting the detrended data respectively. Then, Monte Carlo simulation is used with Simetar© software (Richardson 2010) to estimate the appropriateness of the methods used, the fair insurance premium rates for the Dungeness crab yield insurance, and the probabilities of the indemnified events occurring against the revenue losses.

IV.3 Data Description

The data set analyzed in this study has 63 annual observations related to the state-level Dungeness crab landing prices and yields on the West Coast during the period from 1950 to 2012. There are 8 variables: the commercial production of the crab landing in Alaska, Washington, Oregon and California in pounds of round (live) weight and their landing prices (US cent/lb). The historical data on the four state's prices and yields are collected from the National Oceanic and Atmospheric Administration's National Marine Fisheries Service (NMFS).

The four states' original Dungeness crab price and yield time series (without trend removal) between 1951 and 2012 is represented by the dash lines in figure IV.1. The crab price series of each state seems to have trends over time and to be mean non-stationary processes. It is not clear whether or not the processes of the four crab quantity series are non-stationary, but the crab fishermen in each state have encountered periods of high and low production. A steep decline in the crab production is more likely to be faced by the fishermen based on the historical trends in the crab production shown in figure IV.1. Hence, steadying the crab production volume and the crab landing revenue would be very important for the crab fishermen.

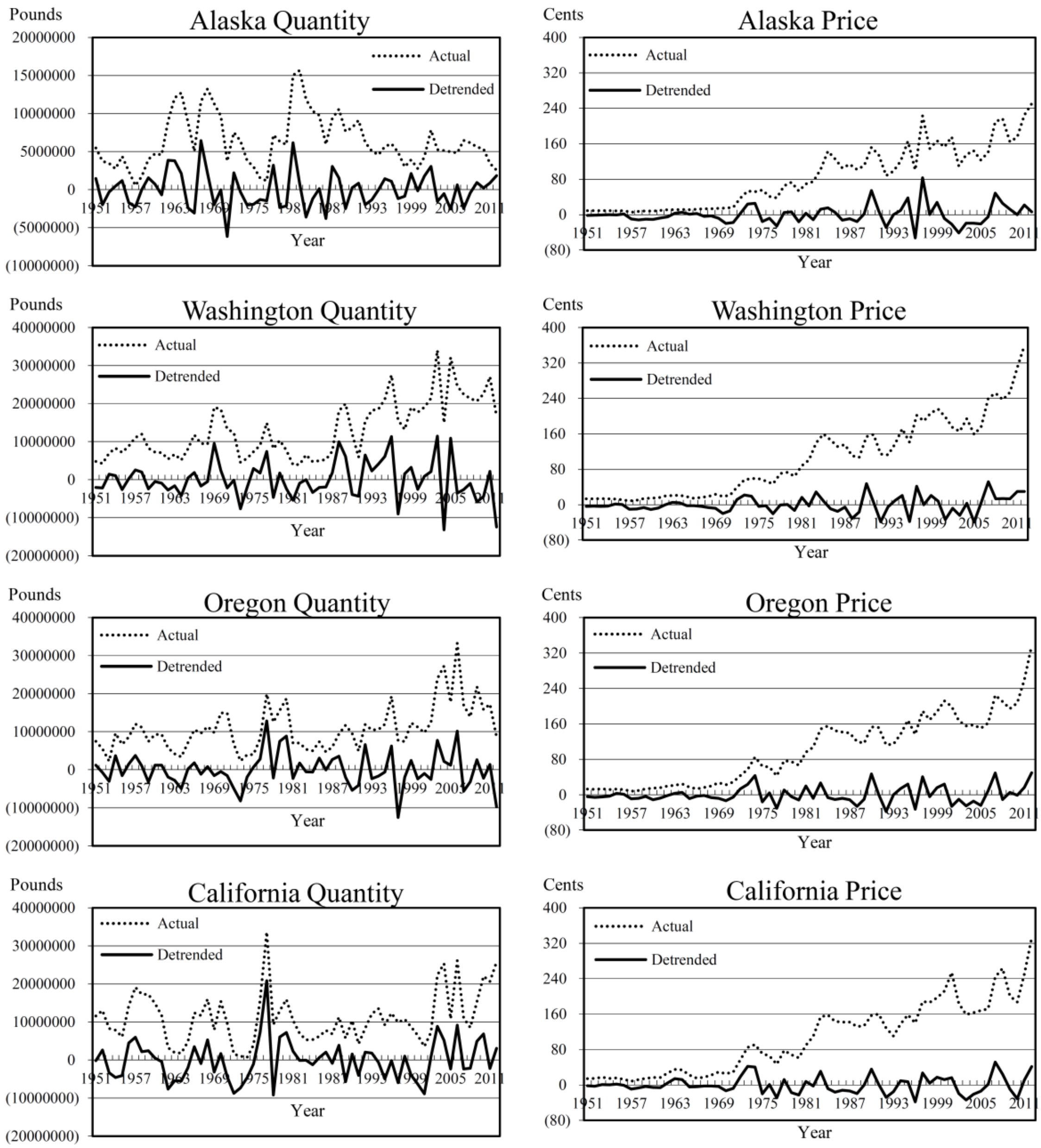

Figure IV.1. Actual and Detrended Data on California, Alaska, Washington, and Oregon Prices and Quantities

Descriptive statistics of the Dungeness crab price and yield data from 1951 through 2012 are summarized in the top half of table IV.1. During this time period, Washington had the highest average crab production volume, followed by California, Oregon and Alaska. Measured by the coefficient of variation expressing the standard deviation as a percentage of the mean, the volumes of crabs caught in California are more volatile than those caught in the other three states. For the four-state crab price comparisons, California had the highest average, followed by Washington, Oregon, and Alaska. It is noteworthy that California with the highest average Dungeness crab price has experienced less volatile prices than the other three states. Alaska with the lowest average price has the second strongest price volatility.

IV.4 Empirical Results

The 63 annual observations between 1950 and 2012 are analyzed for these time series properties using the VECM model. To determine if the VECM model is appropriate for the data on the four states' Dungeness crab landing prices and yields, Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981) for a unit root is applied. The optimal lag lengths for the ADF tests with a maximum of four lags are determined using Bayesian information criterion (BIC). The top half of table IV.2 reports the results of the ADF tests for the four-state crab prices and yields. The levels of the four states' price series are not stationary at the 5% and 1% significance levels. Except for the Washington yields, the null hypotheses of non-stationarity associated with the Alaska, Oregon and California yields are rejected at either the 5% level or both the

5% and 1% levels. The stationary crab yield series may be due to the cyclic fluctuations in the West Coast's Dungeness crab catches. The causes of the cyclic patterns are discussed by Botsford et al. (1998). Nevertheless, if at least two series in the evaluated data are not stationary, a multivariate cointegration model is appropriate (Hansen and Juselius, 1995).

Table IV.1. Summary Statistics of Annual Dungeness Crab Prices (US Cents Per Pound) and Quantities (Pounds), 1951-2012

Variables	Time Series Data			
	Mean	Standard Deviation	Coefficient Variation	
Alaska Quantity (AKQ)	6386321.34	3447231.58	0.54	
Washington Quantity (WAQ)	13052476.44	7454650.09	0.57	
Oregon Quantity (ORQ)	10840393.42	6046495.96	0.56	
California Quantity (CAQ)	11157440.48	6763124.67	0.61	
Alaska Price (AKP)	84. 70	70.00	0.83	
Washington Price (WAP)	104.62	87.43	0.84	
Oregon Price (ORP)	100.56	78.39	0.78	
California Price (CAP)	106.39	80.88	0.76	
	Detrended Data[a]			
	Mean	Standard Deviation	Skewness	Kurtosis
Alaska Quantity (AKQ)	0	2315041.27	0.35	0.75
Washington Quantity (WAQ)	-0	5037178.15	0.15	0.86
Oregon Quantity (ORQ)	-0	4416907.91	0.24	1.45*
California Quantity (CAQ)	-0	5284272.36	0.93*	2.65*
Alaska Price (AKP)	0	21.37	1.14*	3.69*
Washington Price (WAP)	0	18.95	0.37	0.79
Oregon Price (ORP)	0	19.33	0.82*	0.80
California Price (CAP)	0	19.20	0.58	0.37

Note: "*" means the hypotheses of zero skewness and those of zero kurtosis are rejected at the 5% significance level.

[a] The descriptive statistics for the detrended data are calculated with the RATS program.

Table IV.2. Nonstationary Test Results and Trace Tests of Cointegration among Price and Quantity Variables

Variables	Augmented Dickey Fuller Test (with a Constant)		
	T-Statistic	Fail to Reject at 0.05	Fail to Reject at 0.01
AKQ	-3.11 (0)		v
AKP	0.52 (3)	v	v
WAQ	-2.20 (1)	v	v
WAP	1.09 (0)	v	v
ORQ	-4.05 (0)		
ORP	0.80 (0)	v	v
CAQ	-4.35 (0)		
CAP	0.36 (2)	v	v
H_0:Rank	No Constant within the Cointegrating Vectors		
	Trace Test Statistic[a]	C(5%)[b]	Decision
$r = 0$	249.55	155.75	Reject
$r \leq 1$	178.09	123.04	Reject
$r \leq 2$	127.19	93.92	Reject
$r \leq 3$	81.45	68.68	Reject
$r \leq 4$	51.47	47.21	Reject
$r \leq 5$	26.13	29.38	Fail*
$r \leq 6$	12.74	15.34	Fail
$r \leq 7$	3.32	3.84	Fail

Note: Numbers in parentheses are the lags included in ADF test to reach a minimum BIC. The bottom half of table is read from left to right and from the top to bottom. * means the first failure to reject the null hypothesis of the number of cointegrating vectors (r).

[a] Trace refers to the trace statistic considering the null hypothesis that the rank of Π is less than or equal to r.

[b] C(5%) refers to the critical values at the 5 percent level. If the trace statistic exceeds its corresponding critical value, the null hypothesis is rejected.

The optimal lag length k for the VECM model of the equation IV.(1) is one, selected by the BIC with a maximum of four lags. Johansen's trace test is used with the RATS program to determine the number r of cointegrating vectors for no constant within the cointegrating vectors. The outcome of the trace test is provided in the bottom half of table IV.2 which is read from left to right and from the top to bottom. The first failure to reject the null hypothesis in this sequence is less or equal to five, and hence there are five cointegrating vectors without the constant within the cointegration space among the four-state crab price and yield series.

Given the single lag (i.e., $k = 1$) and five cointegrating vectors (i.e., $r = 5$), the set of 62 residuals is obtained from the VECM model and is use as the detrended data. Shown by the solid lines in figure IV.1, the detrended data for the four states' crab prices and yields from 1951 through 2012 fluctuates above and below the zero line. The four moments of each detrended series including mean, standard deviation, skeweness and excess kurtosis are provided in the bottom half of table IV.1. The mean and variance summarize information about the location and variability of a distribution. Each detrended series exhibits a smaller standard deviation with a zero mean as compared to its original time series. The skewness and excess kurtosis are commonly used to describe the shape of a probability distribution.

Skewness is a measure of asymmetry in the probability distribution of the sample data. The negative crop yield skewness is favored in many empirical studies (e.g., Gallagher 1987; Moss and Shonkwiler 1993; Atwood, Shaik, and Watts 2002; Sherrick et al. 2004); it occurs whenever the crop production process is tightly controlled (Hennessy 2009). In contrast to these crop studies, all of the four states' crab price and yield distributions are positively skewed according to the numerical values for skewness in table IV.1. The positively skewed distribution has most of the data clustered to the left, a long tail extending to the right (i.e., a relatively small number of high values), and the mode smaller than the mean and median. Under the null hypothesis of skewness being zero, the four states' Dungeness crab prices and yields are not significantly skewed at the 5% significance level, except for the California production and the Alaska and Oregon prices. Based on the information given above, all of the crab price and yield series are not negatively skewed. The non-negative skewed series seem to imply that the Dungeness crab fisheries on the West Coast could not provide very tightly controlled production and pricing processes.

Excess kurtosis is a measure of the tailedness and peakedness of a data distribution. A distribution with positive excess kurtosis has heavier tails and a higher peak than the normal distribution; while a distribution with negative excess kurtosis has lighter tails and a flatter peak (DeCarlo 1997). Much of the economics literature such as Sherrick et al. (2004) is prone to non-normal kurtosis for crop production. Here, numerically, all the four states have Dungeness crab price and yield values with a positive excess kurtosis. However, this study fails to reject the null hypothesis that the four states' Dungeness crab prices and yield distributions with zero kurtosis at the 5% significance level, except for the Oregon and California yields and the Alaska price. From the kurtosis values and test results, no series has negative excess kurtosis among the crab price and yield data. Then, this study conjectures that probability distributions with negative skewness and negative excess kurtosis may poorly describe the detrended Dungeness crab price and yield data, when combining the skewness and kurtosis results.

The normal and logistic distributions have fixed values for the skewness and kurtosis; while the lognormal, log-logistic, Weibull, inverse Gaussian, and Gamma distributions do not. The above-mentioned seven distributions rely on their own assumptions, properties, and parametric forms of PDF and CDF. The parameters for each of these distributions, for each state's crab price and yield data are estimated using maximum likelihood estimation[28]. Specifically, all these distributions are estimated with the detrended Dungeness crab price and yield data from Alaska, Washington, Oregon, and California, which allows us to compare the different distributions fitted to the same data, the different data fitting the same distributions, and mixture of both.

There are two ways to describe the comparisons between the theoretical and empirical distribution functions: the graphical tools and the goodness-of-fit tests. Here, the Alaska crab yield is taken as an example of the graphical comparisons. Each of the seven probability distributions fitted to the Alaska yield data in both PDF and CDF form is shown in figure IV.2 to illustrate the differences for different parameterizations. The empirical PDF and CDF of the Alaska crab production are shown by the gray histogram with 9 classes[29] and non-smoothed ascending curve respectively. For ease of reference, the four quartiles and the empirical and theoretical distribution functions are included in each panel. As a result, the fitted lognormal with a slightly positive skewness and a slightly positive excess kurtosis appears to represent the Alaska crab yield data

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[28] The @risk software is used in the estimation of the parameters of these two-parameter distributions. Besides, shifting the domain of the distribution is allowed for some probability distributions and the @risk adds a shift factor to these distributions.

[29] The @risk software automatically determines the number of bins (k) with n data points for the chi-square goodness-of-fit test based on the following:

If $n < 35$, k is the nearest integer to $n/5$.

If $n \geq 35$, k is the largest integer below $1.88n^{(2/5)}$.

More information is available at http://kb.palisade.com/index.php?pg=kb.page&id=57. Cited 4 November, 2014.

reasonably well. The fitted inverse Gaussian likewise appears to fit the data well. However, the fitted normal and Weibull have smaller skewness and kurtosis than the fitted lognormal and inverse Gaussian so as to appear to be less well suited in this case. The graphic comparisons of the empirical and fitted distributions are also used for the Washington, Oregon and California crab prices and yields.

While the graphical comparisons between each empirical and theoretical distribution provide useful visual evidence, the goodness-of-fit tests can also be used to provide additional statistical evidence on the adequacy of each theoretical distribution in representing the Dungeness crab price and yield data for each state. The three goodness-of-fit tests used include the Chi-square test with 9 bins, the K-S test, and the A-D test; each of the seven distributions is assigned a fitted rank based the value of the goodness-of-fit test statistic. The rankings of these distributions can be different based on the test used because the three tests meet different fitting criteria for distribution selection. Combining all the results from the three tests, the composite measure are used to compare these probability distributions from the point of view of the sum of three-test ranks for each distribution in each state’s detrended price and yield data.

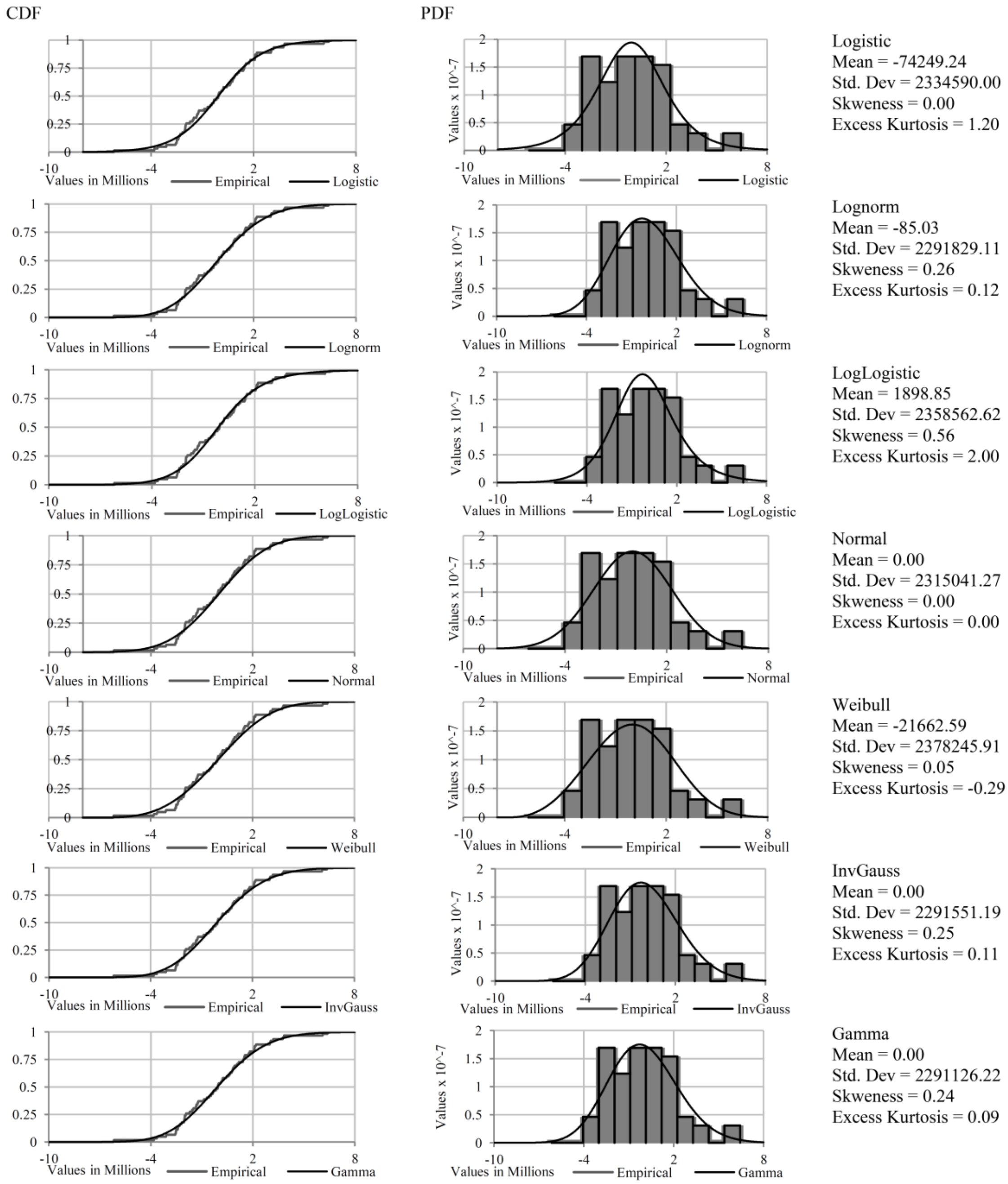

Figure IV.2. Probability and Cumulative Distribution Functions and Empirical Distribution for Dungeness Crab Detrended Yield Data, Alaska, 1951-2012

Table IV.3 shows the individual and composite rankings of alternative distributions of the state-level Dungeness crab prices and yields based on the three goodness-of-fit tests. For the Alaska crab yield, under the Chi-square test, the fitting performance is identical among the logistic, lognormal, inverse Gaussian and Gamma, which ranked first, followed by the normal or Weibull and finally the log-logistic. The results of the Chi-square test are somewhat different compared to those of the K-S and the A-D tests, from which the identical rankings of these fitting distributions are obtained. Nevertheless, there is clear dominance of the logistic over the other distributions under all three goodness-of-fit tests and of course under the composite measure. Similar analyses are used to find the best distribution from the seven probability distributions for the other state-level yield and price variables. For the Oregon yield, the results obtained from the Chi-square, K-S and A-D tests consistently show that the logistic dominates the other theoretical distributions with the Gamma being the worst performer. Due to failed convergence, the Gamma is not fitted to the Oregon yield data. The Gamma also provides the worst fit for the Washington yield data. For the Washington and California yields, the logistics is ranked fifth under the Chi-square test but is ranked first for both the K-S and A-D tests so the composite rank leads to a final overall ranking of logistic. For each of the four western states' Dungeness crab price, although the Chi-square, K-S and A-D tests provide different rankings for the seven distributions, all the three tests consistently rank the log-logistic as the best fitting distribution, and so does the composite measure.

Table IV.3. Goodness-of-Fit Measures and Ranking of Alternative Distributions

Series	Tests	Distributions						
		Logistic	Log-normal	Log-Logistic	Normal	Weibull	Inv Gauss	Gamma
		Ranking Based on Quantity Data						
	χ^2	1	1	7	5	5	1	1
AKQ	A-D	5	1	4	6	7	2	3
	K-S	5	1	4	6	7	2	3
Composite (Sum)		4 (11)	**1** (3)	5 (15)	6 (17)	7 (19)	**2** (5)	3 (7)
	χ^2	5	4	1	2	6	2	7*
WAQ	A-D	1	2	5	4	6	3	7*
	K-S	1	3	2	4	6	4	7*
Composite (Sum)		**1** (7)	3 (9)	**2** (8)	5 (10)	6 (18)	3 (9)	7 (21)
	χ^2	1	2	2	5	4	5	7*
ORQ	A-D	1	2	4	5	6	3	7*
	K-S	1	5	2	4	6	3	7*
Composite (Sum)		**1** (3)	3 (9)	**2** (8)	5 (14)	6 (16)	4 (11)	7 (21)
	χ^2	5	5	7	1	2	3	3
CAQ	A-D	1	2	2	7	6	4	5
	K-S	1	2	4	6	7	3	5
Composite (Sum)		**1** (7)	**2** (9)	4 (13)	6 (14)	7 (15)	3 (10)	4 (13)
		Ranking Based on Price Data						
	χ^2	4	2	1	6	7	2	5
AKP	A-D	2	3	1	6	7	4	5
	K-S	2	3	1	7	6	4	5
Composite (Sum)		**2** (8)	**2** (8)	**1** (3)	6 (19)	7 (20)	4 (10)	5 (15)
	χ^2	2	4	1	3	7	4	4
WAP	A-D	2	3	1	6	7	4	5
	K-S	2	5	1	6	7	3	4
Composite (Sum)		**2** (6)	4 (12)	**1** (3)	6 (15)	7 (21)	3 (11)	5 (13)
	χ^2	6	4	1	7	5	3	2
ORP	A-D	5	2	1	7	6	3	4
	K-S	2	3	1	7	6	4	5
Composite (Sum)		5 (13)	**2** (9)	**1** (3)	7 (21)	6 (17)	3 (10)	4 (11)
	χ^2	2	3	1	5	7	3	6
CAP	A-D	5	2	1	7	6	3	4
	K-S	5	2	1	7	6	3	4
Composite (Sum)		4 (12)	**2** (7)	**1** (3)	6 (19)	6 (19)	3 (9)	5 (14)

Note: See table IV.1 for the definition of variables. "*" means that the data could not significantly fit Gamma because of failing to converge. Numbers in parentheses are the sum of the ranks of the Chi-Square, A-D and K-S tests for each state's yield (or price) data.

The analyses can be summarized as follows: First, for the Dungeness crab yield, the lognormal is the best fit for the Alaska yield data and the logistic for Oregon, Washington, and California yield data, respectively. In general, the lognormal is more skewed to right and has higher kurtosis than the normal distribution with zero skewness and zero excess kurtosis, although the two distributions are relatively close. Both the logistic and normal are symmetric distributions but the logistic with excess kurtosis of 1.2 has heavier tails and a higher peak relative to the normal having excess kurtosis of zero. Second, the log-logistic is the best fit for Alaska, Oregon, Washington, and California crab prices, respectively. Like the lognormal, the log-logistic has higher skeweness and kurtosis than the normal distribution.

Before estimating the crab insurance premiums, the validity of the methods used needs to be tested. Thus, a test is conducted to determine if the actual crab data (Y_t) from 1951 to 2012 are statistically equivalent to the estimated values $(\widehat{Y_t})$ that are generated from the VECM model coupled with the simulated residuals from the selected parametric distributions. Two sample t tests for comparing two means of the two groups and F-tests to test for equal variances are used with the Simetar© software to validate the methods used. As shown in table IV.4, the estimated Dungeness crab prices/yields plus the simulated residuals from the selected distribution are not significantly different from the actual crab prices/yields at the 5% significance level. The results imply that the combination of the VECM model and these parametric distributions provides appropriate analyses of the historical Dungeness crab prices and yields during the period between 1951 and 2012 in each western costal state.

Table IV.4. Comparisons between the Estimated Data and the Actual Data from 1951 to 2012

Variables	Test Value	C(5%)[b]	P-Value	Decision
		Two Sample t Test		
AKQ	0.61	2.27	0.55	Fail
WAQ	0.66	2.27	0.51	Fail
ORQ	1.05	2.27	0.29	Fail
CAQ	0.93	2.27	0.35	Fail
AKP	-0.23	2.27	0.82	Fail
WAP	-0.60	2.27	0.55	Fail
ORP	0.74	2.27	0.46	Fail
CAP	-0.44	2.27	0.66	Fail
		F Test		
AKQ	1.10	1.53	0.35	Fail
WAQ	1.14	1.53	0.31	Fail
ORQ	1.01	1.53	0.48	Fail
CAQ	1.01	1.53	0.48	Fail
AKP	1.08	1.53	0.38	Fail
WAP	1.25	1.53	0.19	Fail
ORP	1.24	1.53	0.20	Fail
CAP	1.06	1.53	0.41	Fail

Note: See table IV.1 for the definition of variables.

[a] C(5%) refers to the critical values at the 0.05 level. If the test value exceeds its critical value, the null hypothesis is rejected.

The indemnity payment for equation IV.(5) is made up of the five parts: the selected yield coverage level, each state's annual average Dungeness crab yield during 2003-2012, its 2013 crab price forecast in light of the VECM model, and its simulated detrended price and yield. Equation IV.(5) is simulated 500 times for the yield coverage levels of 50%, 60%, 70%, and 80%. The probability that the simulated values of the indemnity for each state and for each yield coverage level are greater than zero is calculated as the probability of the indemnity being paid to each state's crab fishermen at the given yield coverage level. The average indemnity derived from each state's 500 simulations at each coverage level divided by its 2003-2012 average yield for each state, respectively, is calculated as the Dungeness crab insurance premium given in cents per pound for each western coastal state for the given percent yield coverage levels. Table IV.5 shows the expected insurance premiums for each state's Dungeness crab yield insurance levels and the probability that the indemnities occur in each state at the four yield coverage levels. For example, if the 80% yield coverage level is selected, the probabilities of the occurrence of indemnified events against the fishermen's revenue losses in Alaska, Washington, Oregon, and California are 35%, 17%, 16%, and 23%, respectively (especially in 2013). Buying the Dungeness crab yield insurance with the 80% yield coverage level, the Alaska, Washington, Oregon, and California Dungeness crab fishermen would pay annual insurance premiums of 31.10, 8.16, 8.03, and 15.42 cents per pound of insured crab production, respectively. The premiums for the 80% yield coverage level in Alaska, Washington, Oregon, and California occupy 10%, 2%, 2% and 4% of its own 2013 expected price per pound, respectively. Typically, at any yield coverage level, Alaska has the highest Dungeness crab yield insurance premium and the highest probability of the insurance company paying indemnities, followed by California, and then Washington or Oregon. The fishermen in Alaska would pay at least twice the insurance premium rate compared to the other states. If the yield coverage level of 50% is selected, the insurance premium of Alaska is up to 13 times greater than what would be required in Washington or Oregon. At each of the four yield coverage levels, the amount that would be paid for the Dungeness crab insurance in Washington is very close to the premium that would be paid in Oregon.

Table IV.5. Insurance Premiums for Dungeness Crab and Probabilities of Paying Indemnities Based on the Yield Coverage Level of 80%, 70%, 60%, and 50%

Coverage Level	States			
	Alaska	Washington	Oregon	California
Insurance Premiums (Cents Per Pound)				
80%	31.10	8.16	8.03	15.43
70%	21.36	3.49	3.73	8.39
60%	14.09	1.55	1.62	4.47
50%	8.79	0.64	0.66	2.22
Probability of Paying Indemnities				
80%	34.6%	17.0%	16.4%	22.8%
70%	26.6%	7.8%	7.4%	13.6%
60%	20.0%	3.4%	3.2%	7.8%
50%	13.2%	1.4%	1.6%	3.8%

IV.5 Conclusion

The Dungeness crab is one of the important commercial fish species along the West Coast. Based on the NMFS annual catch records, the Dungeness crab yields fluctuate dramatically from year to year with cyclic patterns in Alaska, Washington, Oregon and California. A sudden and steep decline in the crab yield is very possible. The crab fishermen are at risks of yield and revenue losses but do not have the option to buy a crab-yield insurance policy. This motivated us to estimate the insurance premiums for the Dungeness crab yield insurance and the probabilities of the occurrence of the fishermen's yield losses covered by the indemnities in each western coastal state at the four yield coverage levels.

From the model applications, the VECM model is conducted to obtain the detrended Dungeness crab price and yield data. The parametric probability distributions best describing these detrended data are found using the goodness-of-fit measures including the Chi-square, K-S, A-D tests. The crab insurance premiums with yield coverage level of 50%, 60%, 70%, and 80% and the probabilities of the realized revenue falling below the insured revenue for the given coverage levels are all estimated.

For the empirical analysis, each state's Dungeness crab price and yield distributions have neither negative skewness nor negative excess kurtosis. The non-negative skewness implies that the Dungeness crab production and pricing processes could not be tightly controlled in each of the four states; the non-negative kurtosis show that the price and yield distributions without the kurtosis less than zero do not have lighter tails and a flatter peak.

It is impossible that the probability distributions with negative skewness and kurtosis can describe the detrended Dungeness crab price and yield well. According to the three goodness-of-fit tests, the lognormal distribution with positive skewness and positive excess kurtosis is the best fit for the Alaska yields; the logistic distribution having no skewness and excess kurtosis equal to 1.2 is the best fit for Oregon, Washington, and California yields, respectively. The best fitting distribution for each state's crab prices is the log-logistic distribution, which has higher skewness and kurtosis than the normal distribution.

All the results from the two sample t tests and the F tests provide evidence that the combination of the VECM model and the best fitting distributions of these detrended data appropriately describe the Dungeness crab prices and yields during the period from 1951 to 2012. At each of the four coverage levels, Alaska has the highest crab yield insurance premium and the highest probability of the indemnities being paid to the fishermen, followed by California, Washington or Oregon. Alaska's crab insurance premiums are more than twice as much as the other states' at any yield coverage level. The premium paid for the Dungeness crab insurance in Washington is very close to that in Oregon at each yield coverage level.

The four western costal states' Dungeness prices and yields are included in the VECM model to obtain the detrended data. Models of biological systems (e.g., the density-dependent models) could be an alternative for the future studies. The parametric distributions are used in this study to estimate the insurance premiums and the probabilities of paying the indemnities. Further research on the premium estimation could consider the non-parametric distribution, if the sample size is big enough.

CHAPTER V

CONCLUSION

This dissertation consists of three essays on the price-quantity relationships, the prequential relationships of the West Coast Dungeness crab fisheries and the estimation of the crab yield insurance premiums. The main empirical results are described below.

In the first essay, the causal relationships among the four-state Dungeness crab's landing prices and quantities are discovered by the DAGs pattern with PC-LiNGAM algorithm based on the VECM model. The Alaska quantity is viewed as an isolated island that does not affect and is not affected by the other prices and quantities. One of the possible reasons is because of the crab stock collapses in several areas of Alaska. The existence of the tri-state (California, Oregon, and Washington) Dungeness crab committee implies that there would be causal relationships among the three states' markets. The California price blocks the information flow of the prices to the Oregon and California quantities. Each state's own quantity (price) and the Alaska price jointly explain more than 60% of variation in its quantity (price) contemporaneously. At the longer time horizons, the Alaska price is more important to quantities (prices); while the four states' quantities (prices) are less important to themselves, except for the California price. The causal flows among the four states' landing prices and quantities is used to help the crab fishermen to reasonably predict the crab prices and harvests and to assist the state governments in making policies to maintain the crab fishery productivity.

The second essay applies prequential analysis to one univariate model (a random walk) and two multivariate models (a 1-lag VAR and a 2-lag VAR) of the West Coast

Dungeness crab landing prices and quantities. The two probability calibration measures including Pearson's chi-square and K-S tests and DAGs are used to assess the model adequacy. The random walk and the 1-lag VAR are better calibrated than the 2-lag VAR. For the Dungeness crab production, the random walk provides slightly better forecasts than the 1-lag VAR and has the following implications. There are no direct relationships among the four states' crab production but random and large fluctuations in the crab production from one period to the next. However, this year's government interventions such as the four states' crab harvest and price policies may have some effects on the next-year crab production in Washington, Oregon and California. For the Dungeness crab prices, the 1-lag VAR outperforms the random walk, except for the Oregon price. This implies that the 1-lag VAR model is more appropriate to analyze the Alaska, Washington, and California crab prices. All the four states' current crab prices and quantities are important factors and should be considered to predict the crab prices in Alaska, Washington, and California at horizon of one year ahead.

In the third essay, the crab fishermen are at risks of yield and revenue losses but do not have the option to buy a crab-yield insurance policy. We estimate the parametric probability distributions best suiting each state's Dungeness crab prices and quantities, the crab-yield insurance premiums, and the probabilities of paying indemnities. According to the properties of the data, the probability distributions with negative skewness and negative kurtosis did not describe the crab prices and yields well. The lognormal distribution tends to be the best fit for the Alaska yields and the logistic distribution best represents the Oregon, Washington, and California yields. The log-

logistic distribution is ranked as the best fitting distribution for each state's crab prices. At each yield coverage level, Alaska has highest insurance premiums for the Dungeness crab yield insurance and highest probability of the occurrence of the indemnified events against the fishermen's realized revenue less than their insured revenue, followed by California, and then Washington or Oregon. The above information may help USDA-RMB to decide if the Dungeness crab yield insurance should be provided to the fishermen against their yield and revenue losses.

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