
DISSERTATION

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Graduate School of The Ohio State University

By

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* * * * *

The Ohio State University

2002

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ABSTRACT

Agricultural industrialization, the application of modern production methods to agriculture, has fundamentally altered the structure of the U.S. pork industry. While consumers have benefitted, more extensive vertical integration and higher industry concentration raise questions about the competitiveness of first-handler markets for slaughter hogs. In this study we estimate the market power of pork processing firms by adapting to the oligopsony case the New Empirical Industrial Organization (NEIO) model of Steen and Salvanes (1999). They estimate oligopoly power by reformulating within an error correction framework the model developed by Just and Chern (1980), Bresnahan (1982), and Lau (1982). This approach, by accounting for short-run deviations from long-run equilibrium, makes more complete use of the information in the data to yield short- and long-run estimates of market power. The results of our model provide no statistically or economically significant evidence that pork processing firms engaged in anticompetitive conduct during the period from 1988 to 2000.
Agricultural industrialization, the application of modern production methods to agriculture, has fundamentally altered the structure of the U.S. pork industry. While consumers have benefitted, more extensive vertical integration and higher industry concentration raise questions about the competitiveness of first-handler markets for slaughter hogs. In this study we estimate the market power of pork processing firms by adapting to the oligopsony case the New Empirical Industrial Organization (NEIO) model of Steen and Salvanes (1999). They estimate oligopoly power by reformulating within an error correction framework the model developed by Just and Chern (1980), Bresnahan (1982), and Lau (1982). This approach, by accounting for short-run deviations from long-run equilibrium, makes more complete use of the information in the data to yield short- and long-run estimates of market power. The results of our model provide no statistically or economically significant evidence that pork processing firms engaged in anticompetitive conduct during the period from 1988 to 2000.
To my late parents
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PUBLICATIONS

Research Publications


FIELDS OF STUDY

Major Field: Agricultural, Environmental, and Development Economics
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CHAPTER 1

INTRODUCTION

The United States agricultural sector has been revolutionized by a process termed agricultural industrialization. This process refers to the production, coordination, and distribution of food products using modern methods typically associated with industrial manufacturing. The dramatic changes wrought by agricultural industrialization are reflected in the recent experience of the U.S. pork industry.\(^1\) The benefits of industrialization include greater productivity and the availability of higher quality pork products. But other aspects of industrialization raise questions about the structure, conduct, and performance of spot (cash) markets for slaughter hogs.

Unlike most empirical industrial organization studies that focus on monopoly or oligopoly power, the focus here is on the buyer’s side of the market. Indeed, Rogers and Sexton (1994) identify several characteristics of first-handler agricultural markets that leave them susceptible to buyer or oligopsony power: (i) bulky, perishable products that are costly to transport, (ii) processors’ demand for specialized farm products, and (iii) inelastic farm supply. Items (i) and (ii) limit spatial competition amongst buyers, and higher industry

concentration together with (iii) presents “compelling structural evidence of buyer market power” (Rogers and Sexton op. cit., p. 1144).

In the case of the pork industry, hog producers have expressed concerns that pork packing firms have acted anti-competitively to push spot hog prices below competitive levels. These concerns stem largely from structural changes that have occurred as a result of industrialization. In response, the federal government has acted to try to improve the functioning of spot markets. However, the appropriateness of government intervention in the marketplace depends on the degree of industry competition (Paarlberg and Haley 2001), and it is here that empirical analysis has an important role to play in the policy arena. To date most empirical studies of the competitiveness of livestock markets have focused on the beef industry, even though the beef and pork industries share similar structures.

The lack of research attention given to the issue of packer oligopsony power in the pork industry means that not much is known about its extent. The purpose of this study is to bridge this gap in our knowledge by estimating the degree of packer oligopsony power in spot markets for slaughter hogs. The modeling framework uses the comparative statics of changes in supply to identify short- and long-run indices of packer oligopsony power.

The remainder of this paper is structured as follows. In chapter 2 we discuss structural changes in the pork industry that bear directly on the issue of packer oligopsony power. In chapter 3 we selectively review the methods and literature on empirical estimation of market power, paying particular attention to the application of these methods to the food

---

2Packing firms slaughter hogs and separate carcasses for packaging and further processing.

3An example of misguided, but well-intentioned policy is pending legislation contained in the Senate version of the farm bill that would outlaw captive supplies. The proposed legislation is intended to improve competition in livestock markets, though the likely impacts are higher industry costs and reduced demand for pork products (Sparks Companies, Inc. 2002).

and related industries. In chapter 4 we describe the empirical model used to estimate packer oligopsony power. In chapter 5 we discuss some concepts from time series econometrics that are important in the context of error correction modeling. In chapter 6 we describe the data used in the analysis. In chapter 7 the empirical results are discussed. Finally, in chapter 8 we conclude the study by reflecting on the method used to estimate oligopsony power.
CHAPTER 2

STRUCTURAL CHANGE IN THE PORK INDUSTRY

The two principal characteristics of industrialization that bear directly on the issue of packer market power in the pork industry are changes in the methods packers use to procure hogs and higher concentration in pork packing. Changes in consumer preferences largely account for recent changes in procurement, whereas packer concentration has been driven by technology-related economies of scale and price competition in output markets.

2.1 Changes in Hog Procurement

Historically, the slaughter hog trade has been a commodity business dominated by spot markets. Hogs were sold on a live-weight basis to middlemen at rural auctions or in urban terminal markets, e.g., the Chicago Stockyards, located adjacent to packing plants and rail lines. However, lower costs resulted in the movement of packing plants from the cities to rural locations in the upper Midwest (Azzam 1998a). The share of hogs sold at auctions or in terminal markets has declined steadily over the years, falling to 3.2 percent in 1998 (USDA-GIPSA 2000, table 2). Today most spot transactions are negotiated between producers and packers with hogs delivered directly to the packing plant. In the early 1990s the pace of industrialization accelerated, resulting in a large decline in spot market volume.
Spot transactions as a share of slaughter declined from 86.6 percent in 1993 to 17.3 percent in January 2001. (Hayenga et al. 1996; NPPC 2001).

Today many packers have vertically integrated upstream into hog production.\(^5\) Hogs that are owned or controlled by packers at least fourteen days prior to slaughter are termed captive supplies (USDA-GIPSA 2002, p. vi). Marketing contracts are the most common type of captive supply arrangement. A typical marketing contract runs from four to seven years and stipulates the producer compensation scheme, risk sharing provisions, minimum number of hogs to be supplied per time period, and minimum standards for hog quality (Hayenga et al. 1996). Fully 82.5 percent of hogs were sold under some type of marketing contract in January 2001 (NPPC 2001). At the same time that spot market volume was falling, captive supplies as a share of slaughter increased from 13.4 percent in 1993 to 82.7 percent in January 2001 (Hayenga et al. op. cit., p. 16; NPPC op. cit.).

Several factors account for the growth in captive supplies. First, the presence of economies of scale in production and packing (see section 2.2) mean that producers and packers face financial losses from running plants at other than minimum efficient scale. Captive supplies better coordinate the flow of hogs from producers to packers by guaranteeing that producers have access to shackle space in packing plants and that packers have a steady supply of hogs. Second, consumers today are more health conscious and lead faster-paced lives, and these changes are reflected in consumer demand for food products. Consumers want food products that are nutritious, safe, tasty, convenient to prepare, and affordable (Kinsey 1994).

These changes brought about the need for a new pork supply system that could better communicate more stringent consumer demand to hog producers. In this regard the

\(^{5}\)Like Love and Burton (1999), we follow Tirole (1988) and use vertical integration in its broadest sense to include ownership and vertical contractual relationships.
system of open markets coordinated by spot prices largely failed. Consequently, packers turned to captive supply arrangements and/or alternative pricing mechanisms in an attempt to improve hog quality.\(^6\)

Carcass-merit pricing is an example of such an alternative pricing system made possible by advances in technology. Under this system the net price received by producers equals the price for a base market hog adjusted for carcass quality.\(^7\) Lawrence et al. (1998) estimate that approximately 73 percent of all hogs were priced on a carcass-merit basis in 1997. Given the importance of product quality, a disadvantage of marketing contracts and carcass pricing is that they give the packer little or no control over the production process. Production contracts provide a solution to this problem. Under this type of arrangement the packer retains ownership of the hogs but contracts with independent producers to raise the animals to market weight. A typical contract specifies the production inputs to be provided by each party, the production process, and producer compensation.\(^8\)

A third reason for captive supplies is exertion of packer market power. This view is reflected in a 1996 U.S. Department of Agriculture (USDA) report on concentration in agriculture, which states in part:

Captive supplies and other forms of vertical integration and coordination at levels in which they occur—in some regions and at some times of the year—are potentially detrimental to both competition and price discovery. These ar-

\(^6\)Hennessy (1996) explains the shift away from spot markets by arguing that imperfect quality measurement dulls producer incentives to invest in quality improving technologies; producers underinvest in quality because they are unable to fully capture the benefits from their investments. On the other hand, packers benefit substantially from higher hog quality. Martinez et al. (1998) cite results from a 1992 National Pork Producers Council (NPPC) study showing that packers could save an estimated “$6.32 per head by slaughtering a hog that is approximately 19% leaner than average.”

\(^7\)The Iowa-Southern Minnesota spot market uses as its base market hog a plant-delivered hog yielding a 185 lb. carcass with 0.9-1.1 in. back-fat and a 6 square inch loin/2.0 depth. Base hog prices are determined in direct negotiations between producers and packers. Because they are established before adjustments for carcass quality, base prices ideally reflect supply and demand conditions in spot markets.

\(^8\)Typically, packers provide the hogs or breeding stock, feed, veterinary care, and management services. Producers provide facilities and labor.
rangements have a tendency to thin market price reporting (reduce the volumes on which reported prices are based) and shorten the weekly marketing “window,” which can disadvantage suppliers who do not have a packer arrangement and distort reported market prices downward [emphasis added] (USDA-AMS 1996).

The current structure of hog procurement does in fact give packers an incentive to exert downward pressure on hog prices. Hogs sold under a formula price contract, a type of marketing contract, accounted for 54.0 percent of slaughter in January 2001 (NPPC 2001). But base prices in many formula price contracts are tied to spot markets. Adding the 54 percent share of formula price contracts to the 17.3 percent share of spot markets implies that spot markets played a role in establishing prices for 71.3 percent of slaughter hogs, hence the incentive for packers to engage in price manipulation.

Several studies, both theoretical (Love and Burton 1999; Zhang and Sexton 2000; Azzam 1998b) and empirical (Ward et al. 1998; Schroeter and Azzam 1999), have investigated the effect of captive supplies on spot prices, though most of this research has focused on the beef industry. Nevertheless, the results are instructive for the pork industry.

Love and Burton (1999) extend Perry’s (1978) model of partial backward integration by a profit maximizing monopsonist to the case of a dominant packer facing a competitive fringe. The dominant packer exerts monopsony power in spot markets and partially integrates backward into livestock production to internalize the associated efficiency losses. However, the ultimate effect of vertical integration (captive supplies) on spot prices depends on changes in the elasticities of the dominant packer’s input demand and residual input supply curves.

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9The price established in the Iowa-Southern Minnesota price market—the largest spot market in the U.S.—serves as a benchmark for many formula price contracts (Schroeder and Mintert 1999).
Zhang and Sexton (2000) use a multi-stage noncooperative game-theoretic approach to develop a duopsony model of spatial price discrimination in livestock markets. If transport costs are high enough then establishment of captive supply regions acts as a “geographic buffer” that reduces price competition among packers. In equilibrium, packers pay the monopsony price to producers located close to the packing plant and offer captive supply contracts that pay higher prices to more distant producers.

Azzam (1998b) adapts Gardner’s (1975) one output two inputs model to a partially integrated oligopsonistic processing industry and derives an expression for the elasticity of the spot market price with respect to the degree of vertical integration. Paradoxically, Azzam finds that an inverse relationship between spot prices and the degree of vertical integration can exist even in the absence of imperfect competition.

Ward et al. (1998) use a general supply-demand model and daily transaction data from April 1992 to April 1993 for the 43 largest beef packing plants to estimate the effect of captive supplies on spot prices. The authors find a small negative relationship between the percentage of captive supply deliveries and spot prices. Schroeter and Azzam (1999) conducted a similar study of beef packing plants and cattle feeders in the Texas panhandle for USDA. Their study also found that larger captive supplies are associated with lower spot prices, though Schroeter and Azzam suggest that this relationship may be due to the timing of captive supply deliveries. Both of these studies used reduced form models to estimate the effect of captive supplies on spot prices. However, such models are incapable of establishing causal relationships. Furthermore, Azzam’s finding of an inverse relationship between spot prices for livestock and vertical integration even when markets are competitive suggests that reduced-form models should not be used for policymaking purposes.
2.2 Industry Concentration

Another characteristic of agricultural industrialization that bears on the issue of packer market power is rising concentration in the packing sector. MacDonald and Ollinger (2000) attribute higher packer concentration to economies of scale and strong price competition in output markets that drove smaller and less efficient plants out of business. Hayenga (1998), using data from 1996–97, estimated that double-shift plants have a $5 per head cost advantage over single-shift plants.

Data from the U.S. Department of Agriculture’s Grain Inspection Packers and Stockyards Administration (USDA-GIPSA) show that both the number and size distribution of packing plants reporting to the federal government changed significantly in recent years. Between 1977 and 1998 the number of plants declined from 469 to 182, while plants with annual slaughter capacities of at least 1 million hogs increased their share of reported annual slaughter from 37.7 percent to 89.8 percent (USDA-GIPSA 2000, tables 19, 24). Concentration at the firm and industry levels also increased markedly. Between 1988 and 1998 the top four firms increased their share of total commercial slaughter from 33.5 percent to 53.9 percent, while the Herfindahl-Hirschman index (HHI) of industry concentration more than doubled from 456 to 960 (USDA-GIPSA op. cit., table 31).

Table 2.1 on the following page shows that the top ten packers dominated the industry in 2000, accounting for 86.4 percent of slaughter capacity.

Perhaps most worrisome about higher packer concentration is research showing that

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10 Concentration in hog production has also increased, though not to the extent that it has in pork packing. In testimony before the Senate Committee on Agriculture, John Caspers, a member of the board of directors of the NPPC, estimated that concentration in hog production had increased to 18 percent from negligible levels in the 1980s (U.S. Congress 2000).

11 The HHI equals the sum of each firm’s squared market share of total commercial slaughter.

12 The corresponding shares in recent years were 82.0% in 1997, 82.3% in 1998, and 86.2% in 1999.
<table>
<thead>
<tr>
<th>Rank</th>
<th>Company</th>
<th>Capacity</th>
<th>Share</th>
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<tr>
<td>1</td>
<td>Smithfield Foods</td>
<td>80,300</td>
<td>21.3%</td>
</tr>
<tr>
<td>2</td>
<td>IBP&lt;sup&gt;b&lt;/sup&gt;</td>
<td>69,500</td>
<td>18.4%</td>
</tr>
<tr>
<td>3</td>
<td>Swift</td>
<td>39,400</td>
<td>10.4%</td>
</tr>
<tr>
<td>4</td>
<td>Excel</td>
<td>38,700</td>
<td>10.2%</td>
</tr>
<tr>
<td>5</td>
<td>Hormel</td>
<td>31,600</td>
<td>8.4%</td>
</tr>
<tr>
<td>6</td>
<td>Farmland</td>
<td>22,800</td>
<td>6.0%</td>
</tr>
<tr>
<td>7</td>
<td>Seaboard</td>
<td>16,000</td>
<td>4.2%</td>
</tr>
<tr>
<td>8</td>
<td>Indiana Packers</td>
<td>11,000</td>
<td>2.9%</td>
</tr>
<tr>
<td>9</td>
<td>Sara Lee</td>
<td>9,000</td>
<td>2.4%</td>
</tr>
<tr>
<td>10</td>
<td>Lundy’s</td>
<td>8,000</td>
<td>2.1%</td>
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<td>Top ten firms</td>
<td>326,300</td>
<td>86.4%</td>
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<tr>
<td>—</td>
<td>Industry Total</td>
<td>377,620</td>
<td>100.0%</td>
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Source: NPPC (2000, p. 25)
<sup>a</sup> Number of hogs
<sup>b</sup> Since acquired by Tyson Foods

Table 2.1—Estimated daily slaughter capacity, June 2000

Oligopoly price markups and oligopsony price markdowns are inversely related to the HHI (Cowling and Waterson 1976; Chen and Lent 1992).

### 2.3 Summary

The effects of agricultural industrialization on the pork industry raise a number of issues and concerns. First, spot markets have in effect become a residual market outlet, though the Iowa-Southern Minnesota market remains active. Second, evidence that the quality of hogs sold in spot markets had declined (Schroeder and Mintert 1999) taken together with lower spot market volume called into question the accuracy of reported market information. Third, because large producers account for the largest shares of captive supplies and slaughter (Lawrence <i>et al.</i> 1997), spot markets have also become the principal domain of small producers. Owing to questions about the accuracy of spot market information,
these producers may be at an informational disadvantage to larger and more market-savvy packers, leaving spot markets vulnerable to packer price manipulation.

Questions about the competitiveness of spot hog markets became more urgent in late 1998, when real hog prices declined to record low levels. At the same time, retail pork prices remained relatively stable, enabling packers to earn large profits while producers incurred large losses, a situation that prompted complaints from pork producers and expressions of concern from legislators about buyer concentration and competitiveness in livestock markets. In remarks before a January 26, 1999 hearing on concentration in agriculture before the Senate Committee on Agriculture, Nutrition, and Forestry, Senator Tom Harkin (D-IA) stated:

It is inevitable that any industry will change over time. That is particularly so in an industry such as agriculture, which has been transformed by revolutionary technological developments. Clearly, technology has been a driving factor in the consolidation of farming operations over the years. But the economic concentration we are so greatly concerned about today is a different matter. History teaches us there is an inherent danger in this economic concentration. The danger, of course, is that economic power will be abused to tilt the playing field, to undermine fair competition and ultimately to detract from the efficiency of a market-based economy. Those dangers are today’s realities.

During the same hearing, Donna Reifschneider, then President of the NPPC, testified that “[p]ork producers believe the time has come to demand real transparency in the marketplace. We feel this is the only way for independent producers to regain and maintain their rightful position as the profit center of this industry. Accurate and timely information will give producers the tools they need to make the marketing decisions appropriate for their operations.”

Congress responded to these concerns by passing the Livestock Mandatory Reporting Act of 1999 as part of the agricultural appropriations bill for fiscal year 2000. The bill was signed into law by President Clinton on October 22, 1999. The legislation requires
packers to report to USDA details of daily hog purchases and slaughter including quantities purchased and slaughtered, prices, and carcass merit premiums and discounts. The purpose of the legislation is to improve competition in livestock markets by providing producers with more accurate and timely market information. Whether the legislation achieves its stated goal, however, is open to debate. Wachenheim and DeVuyst (2001) cite two potential pitfalls. First, confidentiality provisions that protect the identities of individual packers could result in data that is too highly aggregated to be of use to producers selling in local markets. Second, information that is of a sufficiently disaggregated nature coupled with high packer concentration may foster tacit collusion amongst packers bidding in livestock markets.\textsuperscript{13}

Taken individually, either one of larger captive supplies or higher packer concentration would merit some concern about packer market power. But the presence of both phenomenon, each one to some extent reinforcing the other, further bolsters this concern.\textsuperscript{14} However, we would be remiss if we did not mention, as do Love and Burton (1999), that captive supplies have perfectly legitimate uses in some circumstances—such as in assuring hog supplies or in improving quality control—and that falling spot prices may be an unintended consequence of packer use of such arrangements. Nevertheless, the theoretical studies cited in section 2.1 illustrate that captive supplies do have a strategic rationale and that their usage should be monitored, especially in markets that contain structural barriers to competition. It seems apparent, then, that the combination of larger captive supplies and

\textsuperscript{13}This second possibility is more than mere theoretical speculation. Albaek \textit{et al.} (1997) argue that public reporting of concrete prices by the Danish antitrust authority in 1993 led to reduced price competition by concrete manufacturers and higher prices.

\textsuperscript{14}By virtue of the size of their investments, large firms have greater exposure to financial risk than their smaller competitors. To the extent that these risks can be managed with captive supply arrangements further encourages their use. Lower risk exposure in turn encourages investments in new technology that both enables the production of high quality pork products and gives rise to additional economies of scale, the latter promoting still higher industry concentration.
higher packer concentration warrants enough concern about competition in slaughter hog markets to justify an empirical analysis of packer oligopsony power.
In this section we discuss the methodology of the two competing paradigms used by industrial organization economists to analyze market power. We start with the structure conduct performance paradigm (SCPP) originally developed by Mason (1939, 1949) and later extended by Bain (1951). Following that discussion we move on to an analysis of the new empirical industrial organization (NEIO).

3.1 The Structure Conduct Performance Paradigm

Up until the 1970s most empirical analyses of market power were structured around a framework known as the structure-conduct-performance paradigm (SCPP). The SCPP posits a one-way causal relationship from market structure to conduct to performance. Market structure refers to industry concentration, the extent of product differentiation, and the ease with which new firms can enter an industry. Market structure determines firm or industry conduct, notably pricing policy. Conduct, in turn, determines economic performance, which typically is measured by profits or price-cost margins.

While early SCPP research took the form of industry case-studies, it was Bain (1951) who pioneered the use of statistical methods in SCPP research, using data from a large
sample of industries to examine whether and how much structure and conduct variables affected profits or price-cost margins. A typical SCPP model can be written as:

$$\Pi_i = \alpha_i + \beta S_i,$$

(3.1)

where $\Pi_i$ measures average accounting profits in industry $i$, $S_i$ is industry concentration, and $\alpha_i$ represents all other factors affecting industry profitability (Geroski 1988). A positive estimate of $\beta$ provided evidence of anticompetitive industry conduct: higher industry concentration, the argument ran, facilitated collusion, which, in turn, led to higher industry profits in the long run.

While the SCPP has been subject to a variety of criticisms, perhaps the most serious problem stems from the work of Cowling and Waterson (1976) and Clarke and Davies (1982) who showed that all variables in these models are logically endogenous.\(^{15}\) Cowling and Waterson (1976) sought to give SCPP models a sound theoretical underpinning. They showed that a static oligopoly model implies a positive relationship between the Lerner index and the Herfindahl index of industry concentration. In its most familiar form, the Lerner index equals the difference between price and marginal cost as a proportion of price, which, for a monopolist, is given by:

$$\frac{P - c}{P} = \frac{1}{\eta},$$

where $P$ is price, $c$ equals marginal cost, and $\eta$ is the price elasticity of demand. Assuming that firms maximize profits and that marginal cost is constant and equal to average variable cost, Cowling and Waterson derived the industry average equilibrium condition:

$$\frac{\Pi + F}{R} = \frac{H}{\eta} (1 + \mu).$$

(3.2)

\(^{15}\)See Schmalensee (1989) for a detailed critique of empirical research based on the SCPP.
where \( \Pi \) equals industry profit, \( F \) is fixed cost, \( R \) is total revenue, \( H \) is the Herfindahl index, and \( \mu \) is a weighted conjectural variations term that reflects the degree of industry competitiveness. For given values of \( \eta \) and \( \mu \), (3.2) shows that the Lerner index is positively related to the Herfindahl index.\(^{16}\) Clarke and Davies (1982) extended this model to allow for a range of tacitly collusive behavior. In their model the analogue of equation (3.2) is:

\[
\frac{\Pi + F}{R} = \frac{H(1 - \alpha)}{\eta} + \frac{\alpha}{\eta},
\]

where \( \alpha \) indexes the degree of tacit collusion and nests Cournot competition \((\alpha = 0)\) and perfect collusion \((\alpha = 1)\) as special cases. The key insight of Clarke and Davies follows from the expression they derive for \( H \):

\[
H = \frac{1}{N} + \left\{ 1 - N \frac{(\eta - \alpha)}{(1 - \alpha)} \right\}^2 \frac{v_c^2}{N},
\]

where \( v_c^2 \) measures the coefficient of variation of industry marginal costs and \( N \) equals the number of firms. Clearly, \( H \) is endogenous since it depends on all structural parameters of the model. Substituting (3.4) into (3.3) shows that the Lerner index is also endogenous, since it too depends on all structural parameters of the model. Since the Lerner and Herfindahl indices are determined endogenously in this model, it is impossible to infer the direction of causality between structure and performance, and, hence, the nature of industry competition.

### 3.2 The New Empirical Industrial Organization

Dissatisfaction with the SCPP as a means of analyzing market power motivated the so-called new empirical industrial organization (NEIO).\(^{17}\) This approach draws on game

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\(^{16}\)Note that the left-hand side of (3.2) can be interpreted as the Lerner index given that marginal cost is assumed equal to average variable cost.

\(^{17}\)See Bresnahan (1989), Slade (1995), and Kadiyali et al. (2001) for reviews of the NEIO literature.
theory to specify structural econometric models of firm behavior in single industries (Bresnahan 1989).\textsuperscript{18} Although game theory has revolutionized industrial organization, game theoretic models often have a multiplicity of equilibria.\textsuperscript{19} The focus on single industries mitigates this problem by using industry knowledge to restrict both the class of models and the solution set. In contrast, SCPP studies typically analyzed a large number of disparate industries, making it difficult to capture inter-industry differences within a single model (Sutton 1990).\textsuperscript{20}

Since the late-1980s, application of the NEIO approach to estimating the extent of market power has become very common in analysis of the food processing and manufacturing industries.\textsuperscript{21} In light of the increased use of this methodology, it is useful to consider it in more detail.

\subsection*{3.2.1 The NEIO methodology}

In order to illustrate the NEIO methodology, we first consider the basic specification of an NEIO oligopoly model for quantity setting firms that produce a homogeneous product.\textsuperscript{22}

In standard theory, a supply curve represents a functional relationship between price and quantity supplied of the form $P = MC(Q)$, where $P$ is price, $Q$ is quantity, and $MC$ is marginal cost. The supply curve of a perfectly competitive firm coincides with that portion

\textsuperscript{18}See Sexton (1994a,b) for a survey of applications of game theory to agricultural markets.

\textsuperscript{19}The folk theorem formalizes this result for repeated games. It states that a possibly infinite number of subgame perfect Nash equilibria exist as long as agents do not discount the future too heavily. Hence, game theoretic models are often subject to the criticism that “anything can happen.” However, much research has been devoted to developing solution concepts that can narrow the range of potential outcomes. Kreps (1990, pp. 95–128) provides an accessible discussion of the issues.

\textsuperscript{20}However, see Sutton (1991) for a book-length treatment of an alternative approach that seeks to reconcile the NEIO approach with the SCPP.

\textsuperscript{21}See, for example, the surveys by Azzam and Anderson (1996) and Azzam (1997).

\textsuperscript{22}The model developed in chapter 4 shows that the NEIO methodology is readily adapted to the analysis of oligopsony.
of the marginal cost curve above average variable cost. In contrast, imperfectly competitive firms do not have supply curves. Instead, these firms have more general supply relations that allow for nonprice taking conduct. More specifically, a supply relation represents the locus of equilibrium price-quantity pairs that results from a profit maximizing firm equating perceived marginal revenue to marginal cost.\(^{23}\) Mathematically, the supply relation for an individual firm can be written as:

\[
P(Q, z) = \frac{\partial C(q_i, w)}{\partial q_i} - \lambda_i \frac{\partial P(Q, z)}{\partial Q} q_i, \tag{3.5}
\]

where \(P(Q, z)\) is inverse industry demand, \(q_i\) is the firm’s output, \(Q = \sum_{i=1}^{n} q_i\) is industry output, \(z\) is a vector of exogenous variables that shift demand, \(\partial C(\cdot)/\partial q_i\) is the firm’s marginal cost, \(w\) is a vector of exogenous cost-shifters, and \(\partial P(\cdot)/\partial Q\) is the slope of inverse industry demand.\(^{24}\)

The parameter \(\lambda_i\) in (3.5) serves as an index of firm conduct and nests perfect competition (\(\lambda_i = 0\)), Cournot competition (\(\lambda_i = 1/n\)), and monopoly (\(\lambda_i = 1\)) as special cases.\(^{25}\) In any given application, the particular form of the supply relation, and hence, the value of \(\lambda_i\), depends on the modeling approach. One variant takes the specification of the supply relation from a single oligopoly theory. A related approach specifies several supply relations, each one corresponding to a particular oligopoly theory, and uses non-nested statistical tests to distinguish among the various specifications (Gasmi et al. 1992; Carter and MacLaren 1997). Another approach estimates \(\lambda_i\) as a continuous parameter—Corts (1998)

\(^{23}\)Perceived marginal revenue is the additional revenue the firm expects to earn by producing an extra unit of output given its beliefs about the nature of competition (Helpman and Krugman 1992, p. 5).

\(^{24}\)Because NEIO models estimate marginal cost, they are not subject to the criticisms of SCPP models that use accounting cost data (see Fisher and McGowan 1983).

\(^{25}\)In fact, \(\lambda_i\) has several interpretations (see the ensuing discussion).
calls this approach the conduct parameter method (CPM) and we will use that terminology here— without explicitly specifying the nature of the underlying game. In this regard, \( \lambda_i \) has two possible interpretations: (i) as a measure of the equilibrium wedge between price and marginal cost, and (ii) as a measure of a firm’s conjectural variations (Bresnahan 1989). This latter interpretation follows from the fact that \( \lambda_i = \frac{dQ}{dq_i} \), which, as Deodhar and Sheldon (1995, 1997) have demonstrated, can also be expressed as \( 1 + v_i \), where \( v_i \) equals the conjectural variation of the \( i \)th firm. However, because there is no underlying theoretical structure to the model, it is not clear that \( \lambda_i \) can measure a firm’s conjectural variations outside the specific market structures mentioned above. For this reason, it has become common to follow the more general interpretation of \( \lambda_i \) as the wedge between price and marginal cost (Perloff 1992).\(^{26}\)

A typical NEIO oligopoly model consists of equations for a demand curve and a supply relation. The simultaneous determination of demand and supply raises the issue of how \( \lambda_i \) is identified. Equation (3.5) illustrates the identification problem. The reduced-form coefficient on \( q_i \), call it \( \pi \), is a composite of the conduct parameter, \( \lambda_i \), and the slope of inverse industry demand, \( \frac{\partial P(\cdot)}{\partial Q} \). Without additional information, the effect of \( \lambda_i \) cannot be separated from \( \pi \). Clearly, the demand equation yields the slope of the demand curve, call it \( \gamma \), which equals \( \frac{\partial Q(\cdot)}{\partial P} \). If marginal cost is constant with respect to output, then \( \lambda_i = \gamma \pi \) (Deodhar and Sheldon 1995).

Following Carlton and Perloff (1994), this simple identification principle is illustrated in figure 3.1 on the next page. Let \( D_1 \) and \( MR_1 \) denote the demand and associated marginal revenue curves, and assume that marginal cost (MC) is constant at some unknown level.

\(^{26}\)Since the term \( \frac{\partial P(\cdot)}{\partial Q} q_i \) on the righthand side of (3.5) equals the difference between price and marginal cost, it follows that \( \lambda_i \) measures the proportion of this difference or the wedge (see Boyer (1996) for a graphical exposition). Also see Helpman and Krugman (1992, pp. 39–40) who show that perceived marginal revenue is a weighted average of price and marginal revenue where \( 1 - \lambda_i \) and \( \lambda_i \) are the weights.
The initial equilibrium point $E^*$ corresponds to a quantity of $Q^*$ and a price of $P^*$. This equilibrium is consistent with perfect competition, where $D_1$ intersects $MC_c$, and monopoly, where $MR_1$ intersects $MC_m$. Consequently, it is impossible to determine the price-cost margin and $\lambda_i$. Now suppose that an exogenous shock causes a parallel shift in the demand and marginal revenue curves from $D_1$ and $MR_1$ to $D_2$ and $MR_2$. In a perfectly competitive market the equilibrium point moves from $E^*$ to $E_c$; quantity increases from $Q^*$ to $Q_c$, but price remains constant at $P_c = P^*$. On the other hand, in an imperfectly competitive market the equilibrium point moves from $E^*$ to $E_m$; quantity increases from $Q^*$ to $Q_m$, as does price, rising from $P^*$ to $P_m$. Thus, figure 3.1 illustrates that $\lambda_i$ can be interpreted as the marginal response of price to changes in demand. In this particular case a parallel shift in demand identifies $\lambda_i$ when marginal cost is constant. When $\lambda_i = 0$ a change in demand elicits no change in price and the market is perfectly competitive. However, when $0 < \lambda_i \leq 1$ price responds to a change in demand, indicating that the market is imperfectly competitive.

Identification of market power becomes more complicated when marginal cost slopes
Figure 3.2–Monopoly power not identified

upward. In these circumstances the more general identification method developed by Bresnahan (1982) is needed.\textsuperscript{27} Figure 3.2 illustrates the method. The initial equilibrium occurs at point ‘a’. Clearly, this outcome is consistent with perfect competition where $D_1$ intersects $MC_c$ and monopoly or oligopoly where $MR_1$ intersects $MC_m$. Now suppose an exogenous change in demand causes a parallel shift of the demand curve from $D_1$ to $D_2$. Although the equilibrium moves from ‘a’ to ‘b’, competition remains indistinguishable from monopoly or oligopoly. A solution to this problem is illustrated in figure 3.3 on the next page. The initial equilibrium again occurs at point ‘a’, which is consistent with perfect competition and monopoly or oligopoly. Now suppose that an exogenous change in demand causes the demand curve to shift and rotate from $D_1$ to $D_2$. Under perfect competition the equilibrium moves from ‘a’ to ‘b’, tracing out the supply curve $MC_c$. In contrast, under monopoly or oligopoly the equilibrium moves from ‘a’ to ‘c’, tracing out the supply relation $S_m$. Thus,

\textsuperscript{27}Just and Chern (1980) were actually the first to develop this principle in their seminal article on oligopsony.
rotation of the demand curve identifies the nature of industry competition, and the vertical shift in demand traces out the corresponding supply relation.\textsuperscript{28}

In most cases researchers lack access to firm-level data and instead must use industry data to estimate supply relations. Aggregating (3.5) over firms yields:

\[
P(Q, z) = \frac{\partial C(Q, w)}{\partial Q} - \lambda \frac{\partial P(Q, z)}{\partial Q} Q. \tag{3.6}
\]

where $\partial C(\cdot)/\partial Q$ is industry marginal cost. However, the existence of an industry marginal cost function implies certain restrictions on firm-level cost functions that are necessary to allow for consistent aggregation over firms (Chambers 1988; Hazilla 1991). Furthermore, problems of interpretation also arise, though typically, equation (3.6) and $\lambda$ are interpreted as industry averages (Chambers 1988; Bresnahan 1989; Hazilla 1991).\textsuperscript{29}

\textsuperscript{28}Lau (1982) provides a formal proof of Bresnahan’s (1982) result.

\textsuperscript{29}This interpretation is not valid if firms are playing a dynamic game. See Corts (1998) and Genesove and Mullin (1998).
The seminal article by Appelbaum (1982) highlights many of these issues. Appelbaum exploited the duality between cost and production functions to derive industry measures of the price-cost wedge and markup for a homogeneous-good, quantity-setting oligopoly. Appelbaum parameterizes conduct with what he terms a conjectural elasticity ($\theta$). The decision to refer to $\theta$ as the conjectural elasticity is rather unfortunate because it once again confuses the issue as to whether $\theta$ measures the price-cost wedge or the conjectural variations of either a firm or an industry. It turns out that $\theta$ is a weighted $\lambda$, where the weights are the output market shares of each firm in the industry. Thus, $\theta$ and $\lambda$ have the same interpretation as a price-cost wedge.\(^{30}\) The model starts with a cost function. Appelbaum assumed that firms have cost functions of the Gorman polar form that allow for consistent aggregation over firms to the industry level. Because these cost functions are dual to a quasi-homothetic technology, marginal cost is constant and thus identification of $\theta$ is straightforward as illustrated in figure 3.1. Application of Shephard’s lemma yields a system of factor demand equations.\(^{31}\) To that system Appelbaum adds a demand curve and supply relation. The main advantage of the Appelbaum method is that it yields more efficient parameter estimates by using cross-equation restrictions between the supply relation and factor demand equations. Using annual data over the period 1947–71, Appelbaum estimated the model for a series of US industries, including textiles and tobacco, using full information maximum likelihood (FIML) methods.

\(^{30}\)Of course, this does not address the general criticism many theorists have of the concept of conjectural variations (Friedman 1983).

\(^{31}\)Shephard’s lemma assumes perfect competition, and indeed the profit-maximization problem in Appelbaum’s model resembles that of a competitive firm, except that in this case firms are not price-takers. Nevertheless, in equilibrium, firms behave “as if” they maximize profits subject to a given output price that equals perceived marginal revenue. By replacing the competitive price with its shadow price (marginal revenue), Appelbaum was able to use duality theory to estimate oligopoly pricing distortions.
At this point, it is useful to consider an alternative interpretation of the conduct parameter \( \lambda \). Subtracting \( \partial C(\cdot)/\partial Q \) from both sides of equation (3.6) and dividing the resulting expression by \( P \) allows us to write the industry supply relation as:

\[
\lambda = -L\epsilon, \tag{3.7}
\]

where \( \epsilon (< 0) \) is the industry price elasticity of demand, and \( L \) is the Lerner index. Since \( 0 \leq \lambda \leq 1 \), it follows that \( 0 \leq L \leq -1/\epsilon \). Thus, equation (3.7) shows that \( \lambda \) can be interpreted as an elasticity-adjusted Lerner index. In contrast to the Lerner index, \( \lambda \) accounts for (a) “markets that have high margins because demand is inelastic” and (b) “markets that have high margins because they are less competitive or perhaps collusive” (Corts 1998). However, in order to distinguish between these two possibilities, information is also needed on at least one of the other parameters in (3.7). Since economic cost and, hence, the Lerner index cannot be directly observed, attention centers on estimates of the conduct parameter and the industry price elasticity of demand.

### 3.2.2 Market Power Estimation in the Food and Related Industries

The seminal articles by Appelbaum (1982), and Bresnahan (1982), have had a profound and lasting effect on the way in which economists approach the estimation of market power. Importantly, both of the methodologies outlined have been frequently applied to estimation of market power in the food and related industries. For example, Schroeter (1988) extended Appelbaum’s model to allow measurement of both oligopoly and oligopsony power in the US beef packing industry, while Azzam and Pagoulatos (1990) generalized Schroeter’s model by using a primal production function approach that allowed for more general forms

\[32\] Notice that \( L = -1/\epsilon \) only for a monopolist. In the more general oligopoly case \( \lambda < 1 \), which implies that \( 0 \leq L \leq 1 \) (Appelbaum 1982).
of market conduct and input substitution. Buschena and Perloff (1991) generalized Bresnahan’s (1982) model, allowing the parameter, $\lambda$, to vary over time with changes in the market, and using a dominant firm and competitive fringe model to estimate oligopoly power in the Philippine coconut oil export industry. Deodhar and Sheldon (1997) also used the Bresnahan model to estimate market power in the world market for soymeal exports, accounting for entry of Argentinian firms into the export market using a technique similar to Buschena and Perloff.

Some estimates of the Lerner index for various food and related industries are listed in table 3.1 on the following page. Albeit selective, several comments can be made concerning these results: first, the majority of the listed studies, and for that matter the studies not included, concern the US food and related industries; second, estimates of the Lerner index vary quite widely over the sample of industries; third, as Sexton (2000) has pointed out, the US meat marketing system, notably beef, has been subject to most analysis, the studies listed in the table only representing a portion of the NEIO literature on this particular industry.\textsuperscript{33} Sexton suggests that this interest has been due in large part to the very large increase in seller concentration in the US beef packing sector, which has resulted in both academic, industry, and political interest in whether market power has been/is being exercised in this particular sector. In summary, if one accepts that the methodology for estimating market power is robust, we have learned a moderate amount about the exercise of market power in the US food-manufacturing sector, meat marketing in particular.

\textsuperscript{33}Other studies not listed include Azzam (1992, 1997), Koontz and Garcia (1997), and Morrison Paul (1999).
<table>
<thead>
<tr>
<th>Study</th>
<th>Industry</th>
<th>Lerner Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gollop and Roberts (1979)</td>
<td>US coffee roasting</td>
<td>0.06</td>
</tr>
<tr>
<td>Sumner (1981)</td>
<td>US cigarettes</td>
<td>0.50</td>
</tr>
<tr>
<td>Appelbaum (1982)</td>
<td>US textiles</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>US tobacco</td>
<td>0.65</td>
</tr>
<tr>
<td>Lopez (1984)</td>
<td>Canadian food processing</td>
<td>0.50</td>
</tr>
<tr>
<td>Roberts (1984)</td>
<td>US coffee roasting</td>
<td>0.06</td>
</tr>
<tr>
<td>Baker and Bresnahan (1985)</td>
<td>US brewing:</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coors (1962–82)</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>Pabst (1962–82)</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>Anheuser-Busch (1962–75)</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>Anheuser-Busch (1975–82)</td>
<td>0.11</td>
</tr>
<tr>
<td>Schroeter (1988)</td>
<td>US beef packing:</td>
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<td>oligopsony</td>
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</tr>
<tr>
<td></td>
<td>oligopoly</td>
<td>0.04</td>
</tr>
<tr>
<td>Karp and Perloff (1989)</td>
<td>Rice export</td>
<td>0.11</td>
</tr>
<tr>
<td>Azzam and Pagoulatos (1990)</td>
<td>US meat (oligopoly)</td>
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</tr>
<tr>
<td></td>
<td>US livestock (oligopsony)</td>
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</tr>
<tr>
<td></td>
<td>US composite meat processing</td>
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</tr>
<tr>
<td>Schroeter and Azzam (1990)</td>
<td>US beef(^a)</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>US pork(^a)</td>
<td>0.47</td>
</tr>
<tr>
<td>Buschena and Perloff (1991)</td>
<td>Philippines coconut oil</td>
<td>0.89</td>
</tr>
<tr>
<td>Wann and Sexton (1992)</td>
<td>US grade pack pears(^a)</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>US fruit cocktail</td>
<td>1.41</td>
</tr>
<tr>
<td>Deodhar and Sheldon (1995)</td>
<td>German bananas</td>
<td>0.26</td>
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<tr>
<td>Bhuyan and Lopez (1997)</td>
<td>US food(^b)</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>US tobacco industries</td>
<td>0.33</td>
</tr>
<tr>
<td>Gohin and Guyomard (2000)</td>
<td>French food retailing:</td>
<td></td>
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<td></td>
<td>dairy products(^a)</td>
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<td>meat products(^a)</td>
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</tr>
<tr>
<td></td>
<td>other food products(^a)</td>
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</tr>
</tbody>
</table>

Thanks to Jeff Perloff (UC Berkeley) for providing much of the data in this table

\(^a\) Estimates based on joint oligopsony/oligopoly power

\(^b\) Bhuyan and Lopez also calculated Lerner indices for 40 4-digit SIC food industries, ranging from 0.72 for cereal preparation to 0.08 for dried fruit and vegetables.

Table 3.1–Estimated Lerner Indices
3.2.3 Discussion of Static NEIO Models

Since static NEIO methods are still widely used, it is important to note some key issues that arise with use and interpretation of these methods.\textsuperscript{34} The first issue concerns whether to model production technology as one of either fixed or variable-proportions. Sexton (2000) has pointed out that some critics have attacked findings of market power in the beef industry as a failure to allow for input substitution in production.\textsuperscript{35} Studies appealing to a variable-proportions technology typically use very aggregate data, where substitution relates to allocation of an input among several end uses. Sexton questions whether this is actually a very relevant way to define both product markets and technology, and suggests that this is part of a much wider problem with many studies in the NEIO literature, where researchers often use poorly defined product markets. For narrowly defined product categories, the scope for input substitution is limited. Indeed, the concept of input substitution assumes technology is fixed (see Blackorby and Russell 1989). To the extent that substitution between material and nonmaterial inputs occurs over time, proponents of modeling a variable proportions technology confuse input substitution with technical change (Sexton and Lavoie 2001).

A second issue is that, with the exception of Karp and Perloff (1989), all of the NEIO studies listed in table 3.1 are static models of oligopsony/oligopoly. A general criticism of these, and other studies in the field, is that they attempt to model dynamic interactions between agents, namely, reactions to each other’s quantity or price strategies in a static

\textsuperscript{34}Note that this is not a comprehensive discussion of all of the issues relating to use of the NEIO methodology, a more thorough discussion can be found in Sexton (2000), and Sexton and Lavoie (2001).

\textsuperscript{35}See, for example, Goodwin and Brester (1995).
framework, using the concept of conjectural variations.\(^{36}\) This is surprising in light of the fact that perhaps the most important advance made in the field of industrial organization has been the ability to analyze multi-period games that have oligopolistic equilibria. In particular, it has been shown that non-cooperative collusive equilibria can be obtained in repeated games (Fudenberg and Tirole 1989). This is reinforced by a recent survey of the empirical industrial organization literature by Slade (1995), suggesting that static one-shot Nash games in either quantities or prices are nearly always rejected by the data.

In contrast to static models, dynamic models attempt to capture the underlying strategic behavior of market participants. A characteristic of dynamic models that has limited their use is the fact that they can be very difficult to solve, and usually require firm-level data. For the sake of tractability, most dynamic models have restricted attention to linear-quadratic games. The term linear-quadratic comes from optimal control theory and refers to a problem where the objective function is quadratic and the constraints are linear.\(^{37}\) The linear-quadratic approach has frequently been used in theoretical models of oligopoly (Fershtman and Kamien 1987; Reynolds 1987; Dockner 1992; and Karp and Perloff 1993a), and has received some limited application in analysis of the food industries (Karp and Perloff 1989, 1993b; and Deodhar and Sheldon 1996). A particular advantage of using this approach is that closed-form solutions can be found for the equilibria of differential games and, therefore, it is possible to solve analytically for a market conduct parameter (Dockner \textit{op. cit.}; Karp and Perloff 1993a,b; Slade 1995).

Notwithstanding this, most researchers continue to use static models to obtain estimates

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\(^{36}\) An additional criticism of this methodology has recently been put forward by Corts (1998). He shows that with high seasonality in demand, it may be incorrect to make inferences about market power based on a conjectural variations approach.

\(^{37}\) In these games the profit function is quadratic in the state and control variables and the equations of motion that describe the evolution of the state are linear in these same variables.
of market power. In this regard, some critics, notably Friedman (1983), have attacked this approach by pointing out that static measures of market power do not contain any information about the dynamics of market interaction. Recent theoretical work, however, has blunted this criticism somewhat. Specifically, Dockner (1992), Cabral (1995), and Pfaffermayr (1997) have shown that static measures of market power are sufficient statistics for an underlying dynamic game.

Finally, there is a key econometric issue relating to the methodology. As Sexton (2000) has pointed out, most NEIO studies are based on specific \textit{ex ante} choices of functional forms and explanatory variables for the demand function, supply relation, and processing technology. Consequently, the NEIO researcher is always testing a joint hypothesis, i.e., a test of whether a market is competitive or not, along with a test of the maintained hypotheses concerning functional form. Sexton suggests that this problem is not too serious in terms of processing technology where researchers have commonly used flexible functional forms, but may be a problem with respect to demand specification, where usually very simple functional forms have been utilized.

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\(^{38}\)There are other practical econometric issues that NEIO research faces, but they are not particularly unique to this line of research.
CHAPTER 4

THE MODEL

The variety of methods available to estimate market power calls into question the suitability of a particular method in a given research setting. Relative to the other methods described in chapter 3, the data requirements of the Appelbaum (1982) method are quite demanding, as a system of factor demands is estimated jointly with supply and demand equations. In addition to the data requirements, the factor demand system typically includes an equation for capital. Bresnahan (1989, p. 1040) points out that in most cases accounting data is used as a proxy for the price of capital services, and, consequently, the Appelbaum method is subject to the same criticisms leveled at the structure conduct performance paradigm over the use of accounting cost data. Other methods, particularly the dynamic oligopoly models developed in Karp and Perloff (1989, 1993a,b) and Deodhar and Sheldon (1996) require firm-level data to estimate the models. However, as was discussed in section 3.2.1, in most cases such data is unavailable, and economists must estimate their models using aggregate industry-level data. In this study, we estimate our model using a variation on the method developed by Just and Chern (1980), Bresnahan (1982), and Lau (1982). Generally speaking, the appeal of this method lies in its modest data requirements and simple functional forms for supply and demand equations.
All of the papers mentioned in the preceding paragraph estimate models using variants of the conduct parameter method (CPM). As is apparent from the discussion in chapter 3, most applications of the CPM yield a single estimate of market power, though some papers have developed models that allow market power to vary with time. For example, in Appelbaum (1982) the conjectural elasticity, θ, varies with changes in input prices. Buschena and Perloff allowed λ to vary with changes in government policy. Azzam and Park (1993) estimated a CPM model using a switching regression technique that allowed λ to vary with structural changes in the beef industry. Useful though these approaches may be, they are subject to the criticism that they are *ad hoc*. Nevertheless, these attempts to account for dynamics highlight the importance of developing theoretically coherent models that account for the fact that market power of firms is unlikely to remain constant. Indeed, firms may have some market power in the short-run, while still acting competitively in the long-run.

The CPM assumes that observed prices and quantities represent a position of market equilibrium. While markets do tend toward equilibrium over the long-run and on average, the reasonableness of this assumption in any particular empirical application depends to a significant extent on the frequency of the data in relation to the adjustment period following a disequilibrium shock (Boyer 1996). For example, the adjustment period may exceed the periodicity of the data, particularly when the data are observed more than once per annum, e.g., monthly or quarterly, and in such circumstances it is important to account for the underlying dynamics. In their paper, Steen and Salvanes (1999) incorporate dynamics by reformulating and estimating within an error correction framework the NEIO model developed by Just and Chern (1980), Bresnahan (1982), and Lau (1982), and that is the approach adopted in this paper. Though not truly a dynamic model, by accounting for short-run deviations from long-run equilibrium, the error correction approach makes more
complete use of the information in the data to yield short- and long-run estimates of market power. Steen and Salvanes used their model to estimate the oligopoly power of Norway in the French market for imported salmon. In this section we adapt their model to the oligopsony case, the first such application of this particular approach.

4.1 Theoretical Specification

The setup of the model follows Schroeter (1988). Assume there are \( n \) (not necessarily symmetric) packing firms in the industry (indexed \( i = 1 \ldots n \)) that produce a homogeneous product, raw pork. Assume further that packing firms use a quasi-fixed proportions technology in which there is a fixed proportional relationship between the material input (hogs) and the output (pork), but that uses other nonmaterial inputs in variable proportions. With the appropriate choice of units the same variable for both the firm \( (q_i) \) and industry \( (Q = \sum_{i=1}^{n} q_i) \) can be used to represent quantities of the material input and output.

Let the industry hog supply curve be given by

\[
Q = h(W_h, z),
\]

where \( Q = \sum_{i=1}^{n} q_i \) is the industry quantity of the material input and the output, \( W_h \) is the hog price, and \( z \) is a vector of exogenous variables that shift supply. Solving (4.1) for \( W_h \) yields the inverse industry hog supply curve:

\[
W_h = g(Q, z).
\]

Assuming competitive behavior in output and nonmaterial input markets, packing firms face the following profit maximization problem:

\[
\max_{q_i} \Pi_i = Pq_i - W_h q_i - C_i(q_i, W) \quad \text{s.t. (4.2)}.
\]
where $q_i$ is the output of the $i$th firm, $P$ and $W$ are the parametric prices of output and non-material inputs, and $C_i(\cdot)$ is total processing cost of the $i$th firm. Differentiating (4.3) with respect to $q_i$, and assuming the second order necessary condition for a unique maximum is satisfied, yields

$$\frac{\partial \Pi_i}{\partial q_i} = P - W_h - q_i \frac{\partial g(\cdot)}{\partial Q} \frac{dQ}{dq_i} - \frac{\partial C_i(\cdot)}{\partial q_i} = 0, \tag{4.4}$$

where $\frac{\partial g(\cdot)}{\partial Q}$ is the slope of the inverse industry hog supply curve, $\frac{dQ}{dq_i}$ is the change in industry quantity with respect to a change in the quantity of the $i$th firm, and $\frac{\partial C_i(\cdot)}{\partial q_i}$ is firm-specific marginal processing cost. Letting $\lambda_i = \frac{dQ}{dq_i}$ and rearranging (4.4) yields

$$W_h + \lambda_i \frac{\partial g(\cdot)}{\partial Q} q_i = P - \frac{\partial C_i(\cdot)}{\partial q_i}. \tag{4.5}$$

Equation (4.5) says that in equilibrium packing firms equate their perceived marginal hog expenditures to the value marginal product (VMP) of output net of marginal processing costs. Solving (4.5) for $W_h$ yields the firm’s derived demand relation:

$$W_h = -\lambda_i \frac{\partial g(\cdot)}{\partial Q} q_i + P - \frac{\partial C_i(\cdot)}{\partial q_i}. \tag{4.6}$$

Since we estimate our model with industry data, we need the industry counterpart to (4.6). Multiplying (4.6) by $Q/Q$ and taking the sum over all firms yields the industry derived demand relation:

$$W_h = -\sum_{i=1}^{n} \lambda_i \frac{q_i}{Q} \frac{\partial g(\cdot)}{\partial Q} Q + P - \sum_{i=1}^{n} \frac{\partial C_i(\cdot)}{\partial q_i}, \tag{4.7}$$

or

$$W_h = -\lambda \frac{\partial g(\cdot)}{\partial Q} Q + P - \frac{\partial C(\cdot)}{\partial Q} \frac{\partial Q}{\partial W_h} \frac{\partial Q}{\partial \text{VMP}}. \tag{4.8}$$
where it is assumed that the conditions for consistent aggregation over firms are satisfied. Notice that $\lambda$ in (4.8) is a weighted average of the $\lambda_i$s, where the weights are each firm’s share of material input usage. The complete model consists of equations (4.1) and (4.8).

Empirical implementation of the model requires choosing functional forms for the hog supply curve and derived demand relation. Typically, linear functional forms are chosen. However, Perloff and Shen (2001) demonstrate that the linear model has severe multicollinearity problems. To avoid these difficulties and to account for possible nonlinearities we use log-linear specifications for supply and demand.

### 4.2 Dynamics of Hog Supply

The specification of hog supply is complicated by the biological lags inherent to hog production. These lags in turn mean that producers must make production decisions based on current expectations of future prices (Holt and Johnson 1988). Holt and Johnson developed a multi-equation model of hog supply response that accounts for the underlying dynamics of hog production, and the model of hog supply developed in this section is based on their work. However, since estimation of hog supply response is not the key focus of this study, our specification of hog supply represents a considerable simplification of the Holt and Johnson model.

The entire production process from farrow-to-finish spans an approximate ten month period and is illustrated in figure 4.1 on the next page. Decisions about the size of the breeding herd determine the size of the subsequent pig crop or the number of pigs born. The gestation period for a sow is roughly four months. Pigs are weaned three to eight

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40 See the discussion in section 3.2.1 above and the associated references.

41 The Holt and Johnson (1988) model consists of seven equations: a deterministic equation for the quantity of pork as well as stochastic equations for the breeding herd, sow slaughter, pig crop, barrow and gilt slaughter, live weight of sows, and live weight of barrows and gilts.
weeks after farrowing, and it takes another four to five months to feed the weaned pigs to market weight (Holt and Johnson 1988).

Pork is produced from barrows and gilts, sows, and stags and boars. Following Holt and Johnson (op. cit.), we specify the supply of pork as a deterministic function of slaughter and average live weights:

\[ Q = BGS \times BGWT + SS \times SWT + SBS \times SBWT, \]

where \( BGS, SS, \) and \( SBS \) are slaughter of barrows and gilts, sows, and stags and boars,
and where \( BGWT, SWT, \) and \( SBWT \) are their respective average weights. During the 1988–2000 period covered by this study, slaughter of barrows and gilts averaged 95.2\% of total slaughter under federal inspection. As a result, we exclude sows and stags and boars from the pork supply equation and instead write it in the simpler form

\[
Q = BGS \times BGWT.
\]

Taking the natural logarithm of this expression yields

\[
q_t = \log(BGS_t) + \log(BGWT_t),
\]

where \( t \) indexes time, and, from this point forward, a lowercase letter denotes the natural logarithm of a variable.

The measure of oligopsony power in equation (4.8), \( \lambda \), is the coefficient of a term that includes the slope of the inverse industry hog supply curve, \( \partial g(\cdot)/\partial Q \). The slope of the long-run hog supply curve can be obtained by differentiating (4.9) with respect to \( w_h \) via the chain rule which yields

\[
\frac{\partial q}{\partial w_h} = \frac{\partial q}{\partial bgs} \cdot \frac{\partial bgs}{\partial w_h} + \frac{\partial q}{\partial bgwt} \cdot \frac{\partial bgwt}{\partial w_h}.
\]

Thus, obtaining an estimate of the slope of the supply curve, and hence \( \lambda \), requires choosing functional forms for \( bgs \) and \( bgwt \).

Recalling that five to six months elapse between farrowing and marketing, Holt and Johnson (1988) surmise that slaughter is a function of the first three quarterly lags of the pig crop. Neither the hog price nor other economic variables are included in the specification because “once pigs are born, little can be done to alter the number of hogs marketed” (Holt
and Johnson *op. cit.*, p. 322). In view of this fact, write the equation for barrow and gilt slaughter as

$$bgs_t = A(L)pc_t + \nu_t,$$  \hspace{1cm} (4.11)

where, for simplicity, we have suppressed the constant, $L$ is the lag operator and is defined as $L^k x_t = x_{t-k}$, $A(L) = \alpha_0 + \alpha_1 L + \alpha_2 L^2 + \alpha_3 L^3$ is a third-order polynomial in $L$, $pc$ is the pig crop, $\nu \sim iid(0, \sigma^2_\nu)$, or independently and identically distributed with mean 0 and variance $\sigma^2_\nu$, and the symbol $\sim$ denotes the distributional properties of the random variable. Setting $\alpha_0 = 0$ yields the specification for barrow and gilt slaughter in Holt and Johnson (*op. cit.*).

In contrast to slaughter, current and lagged hog prices are expected to affect the average weight of barrows and gilts, the idea being that producers have some discretion as to precisely when hogs are marketed. In light of this information, write the live weight equation as

$$bgwt_t = B(L)wh_t + \epsilon_t,$$  \hspace{1cm} (4.12)

where, again, the constant has been suppressed, $B(L) = \beta_0 + \beta_1 L + \beta_2 L^2 + \cdots + \beta_k L^k$ is a $k$th-order polynomial in $L$, $wh$ is the real hog price, and $\epsilon \sim iid(0, \sigma^2_\epsilon)$.$^{42}$

Substituting equations (4.11) and (4.12) into (4.9) and adding a constant ($\mu$), three seasonal dummy variables ($S_i$), and a time trend ($t$) yields

$$q_t = \mu + A(L)pc_t + B(L)wh_t + \sum_{i=1}^3 \pi_i S_{i,t} + \delta t + \eta_t,$$  \hspace{1cm} (4.13)

$^{42}$Equation (4.12) has an autoregressive distributed lag (ARDL) formulation in which one or more lags of the dependent variable appear as regressors. More will be said about the ARDL model in section 4.4.
where $\eta = \nu + \varepsilon \sim iid(0, \sigma^2_\eta)$. In the steady-state equilibrium $pc_{t-1} = pc_{t-2} = pc_{t-3}$, and $w_{ht} = w_{ht-1} = \cdots = w_{ht-k}$. Thus, the long-run effect of the hog price on hog supply equals $\beta_1 + \beta_2 + \cdots + \beta_k$. Substituting the value 1 for $L$ into the expression for $B(L)$ yields the sum of the lag coefficients. Hence the long-run price effect can be written alternatively as $B(1)$. Similarly, the long-run effect of the pig crop on hog supply equals $A(1)$. Imposing the steady-state restrictions on (4.13) yields:

$$q_t = \mu + A(1)pc_t + B(1)w_{ht} + \sum_{i=1}^{3} \pi_iS_{i,t} + \delta t + \eta_t.$$  

(4.14)

Differentiating equation (4.14) with respect to $w_h$ yields the slope of the long-run hog supply curve given by

$$\frac{\partial q}{\partial w_h} = B(1) = \beta_1 + \beta_2 + \cdots + \beta_k.$$  

(4.15)

Thus, the long-run slope is determined entirely by parameters in (4.12). Equation (4.15) in turn implies that the slope of the inverse industry supply curve can be written as

$$\frac{\partial g(\cdot)}{q} = \frac{1}{B(1)} = \frac{1}{\beta_1 + \beta_2 + \cdots + \beta_k}.$$  

(4.16)

### 4.3 Static CPM Model

In this section we develop a simple static oligopsony model in order to highlight the main issues pertaining to the identification and estimation of market power. The model is static in the sense that it yields a single measure of oligopsony power. In section 4.4 we reformulate the static model within an error correction framework.

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Equation (4.13) implies that hog producers do not have fully rational expectations with respect to hog prices. Indeed, Chavas (1999) found that 73% of the market has quasi-rational, or backward looking, price expectations.
Let the derived hog demand curve at time \( t \) be given by

\[
wh,t = \delta_0 + \delta_{10}q_t + \delta_{20}qb,t + \delta_{30}qp,t + \delta_{40}y_t + \delta_{50}w_t + \zeta_t,
\]

(4.17)

where \( q_b \) and \( q_p \) are production of beef and poultry, \( y \) is real per capita income, \( w \) is the real hourly packing plant wage, and \( \zeta \sim iid(0, \sigma^2_\zeta) \) represents other factors that shift derived hog demand.

Equation (4.8) shows that the derived demand relation consists of the hog price, \( W_h \), value marginal product net of processing costs, VMP, and the proportionate wedge between VMP and the hog price, VMP - \( W_h \). Substituting (4.16) into the expression for the wedge in (4.8) and writing \( q \) for \( Q \) yields

\[
-\frac{\lambda}{B(1)} q.
\]

(4.18)

Combining (4.17) and (4.18) and rearranging terms yields the industry derived demand relation

\[
wh,t = \delta_0 + \gamma q_t + \delta_{20}qb,t + \delta_{30}qp,t + \delta_{40}y_t + \delta_{50}w_t + \zeta_t,
\]

(4.19)

where \( \gamma = \delta_{10} - \lambda/B(1) \). Equations (4.14) and (4.19) yield estimates of \( B(1) \) and \( \gamma \). However, without an estimate of \( \delta_{10} \), the coefficient \( \lambda \) is not identified.

The identification problem is illustrated in figure 4.2 on the following page, which is similar to figure 3.2 on page 21 for the oligopoly case. The initial equilibrium is given by point ‘a’. This outcome is consistent with perfect competition where \( S_1 \) intersects VMP\(_c\) and monopsony or oligopsony where MFC\(_1\) intersects VMP\(_m\). Now suppose an exogenous change in supply causes a parallel shift of the supply curve from \( S_1 \) to \( S_2 \). Although the equilibrium moves from ‘a’ to ‘b’, competition and monopsony/oligopsony are observationally equivalent. The solution is similar to that shown in figure 3.3 on page 22 where a
rotation of the demand curve was necessary to identify monopoly power. In this case a rotation of the supply curve is needed as shown in figure 4.3 on the next page. The setup is the same as in figure 4.2. Now suppose that an exogenous change in supply causes the supply curve to shift and rotate from $S_1$ to $S_2$. Under perfect competition the equilibrium moves from ‘a’ to ‘b’, tracing out the derived demand curve VMP$_c$. In contrast, under monopsony or oligopsony the equilibrium moves from ‘a’ to ‘c’, tracing out the derived demand relation D$_m$. Thus, rotation of the supply curve identifies the nature of industry competition, and the vertical shift in supply traces out the corresponding demand relation.\footnote{Note that it is D$_m$ that is estimated econometrically.}

It should be noted that use of this method is dependent on a once-and-for-all shock identifying market power. For example, Just and Chern (1980) were especially fortunate in that they had a natural experiment, introduction of the mechanical tomato harvester, which rotated the tomato supply curve, allowing them to identify oligopsony power of tomato processors. The assumption made here is that the hog supply curve rotates as a result of

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure4_2.png}
\caption{Monopsony power not identified}
\end{figure}
technical change. Typically, a time trend is used as a proxy for technical change, however, in this case we use pigs per litter (see chapter 7). In order to rotate the hog supply curve, suppose that pigs per litter enters (4.12) interactively with \( w_h \):

\[
bgwt_t = B(L)w_{h,t} + \varphi \{ w_{h,t} \cdot pglit_t \} + \epsilon_t,
\]

(4.20)

where \( pglit \) denotes pigs per litter.\(^{45}\) Substituting equations (4.11) and (4.20) into (4.9) and adding a constant, seasonal dummies, and a trend yields

\[
q_t = A(1)pc_t + B(1)w_{h,t} + \varphi \{ w_{h,t} \cdot pglit_t \} + \sum_{i=1}^{3} \pi_i S_{i,t} + \delta t + \eta_t.
\]

(4.21)

The slope of the inverse supply curve is now \( 1/(B(1) + \varphi \cdot pglit) \) and the implied wedge is \( \lambda q^* \), where \( q^* = -q/(B(1) + \varphi \cdot pglit) \). Combining (4.17) and the expression for the implied wedge yields the new industry derived demand relation:

\[
w_{h,t} = \delta_0 + \lambda q^*_t + \delta_{10}q_t + \delta_{20}q_{b,t} + \delta_{30}q_{p,t} + \delta_{40}y_t + \delta_{50}w_t + \varsigma_t.
\]

(4.22)

\(^{45}\)Notice that a rotation of equation (4.20) necessarily causes the hog supply curve to rotate.
The complete static model consists of equations (4.21) and (4.22), the latter of which shows that $\lambda$ is now identified as the coefficient of $q^*$.

### 4.4 The “Dynamic” CPM Model

Equation (4.22) assumes that the endogenous variables $w_h$ and $q$ adjust instantaneously to their long-run equilibrium paths following shocks to the other variables. However, the presence of rigidities such as habit persistence in demand give rise to adjustment costs, the effects of which mean that adjustment from one equilibrium to another generally takes place over a (sometimes extended) period of time. This equilibrium adjustment process provides a justification for the inclusion of lagged variables in our model.

The autoregressive distributed lag (ARDL) specification provides a convenient and flexible framework for modeling the temporal response of $w_h$ to exogenous shocks.\(^{46}\) Consider the ARDL form of (4.22) with two lags given by

$$w_{h,t} = \delta_0 + \lambda_0 q_t^* + \lambda_1 q_{t-1}^* + \lambda_2 q_{t-2}^* + \delta_{01} w_{h,t-1} + \delta_{02} w_{h,t-2}$$
$$+ \delta_{10} q_t + \delta_{11} q_{t-1} + \delta_{12} q_{t-2} + \delta_{20} q_{h,t} + \delta_{21} q_{h,t-1} + \delta_{22} q_{h,t-2}$$
$$+ \delta_{30} q_{p,t} + \delta_{31} q_{p,t-1} + \delta_{32} q_{p,t-2} + \delta_{40} y_t + \delta_{41} y_{t-1} + \delta_{42} y_{t-2}$$
$$+ \delta_{50} w_t + \delta_{51} w_{t-1} + \delta_{52} w_{t-2} + \varsigma_t.$$ \hspace{1cm} (4.23)

Clearly, (4.23) is autoregressive since $w_{h,t-1}$ and $w_{h,t-2}$ appear as regressors. The addition of lagged variables captures the idea that the effect of an exogenous shock on $w_{h,t}$ is spread out or distributed over time.\(^{47}\) To better understand this point, suppose there is a one-unit

\(^{46}\)Hendry (1996) shows that the vector ARDL model nests a number of competing specifications including the static model, the error correction model, and the partial adjustment model, *inter alia*.

\(^{47}\)The ARDL and error correction models are alternative, but equivalent, ways of parameterizing dynamics. Although it is easiest to show this correspondence in a model with only one lag, including two lags yields greater insight into the dynamic properties of error correction processes.
change in $q_t$, ceteris paribus. The immediate or short-run impact of this change on $w_{h,t}$ is $\partial w_{h,t}/\partial q_t = \delta_{10}$, the coefficient of the contemporaneous variable. Following Verbeek (2000, p. 279), it can be shown that the corresponding long-run impact of this change in $w_{h,t}$ is given by

$$\delta_{10} + \delta_{11} + [1 + (\delta_{01} + \delta_{02}) + (\delta_{01} + \delta_{02})^2 + \cdots]$$

$$\times [(\delta_{10} + \delta_{11})(\delta_{01} + \delta_{02}) + \delta_{12}] = \frac{\delta_{10} + \delta_{11} + \delta_{12}}{1 - \delta_{01} - \delta_{02}}$$

(4.24)

if and only if the stability condition $|\delta| < 1$ holds, where $\delta = \delta_{01} + \delta_{02}$.\footnote{If $|\delta| < 1$, the effect of the shock eventually dies out since $|\delta^t| \to 0$ as $t \to \infty$. If $|\delta| > 1$, the shock has an explosive effect since $|\delta^t| \to \infty$ as $t \to \infty$. Alternatively, if $|\delta| = 1$, the shock has a persistent effect and its magnitude increases by $(\delta_{10} + \delta_{11})(\delta_{01} + \delta_{02}) + \delta_{12}$ each period. In the ensuing discussion we assume that the stability condition is satisfied.}

In the steady-state equilibrium the value of each variable in (4.23) is constant, and the long-run solution for the derived demand relation can be written as

$$w_{h,t} = \delta_0 + \lambda_0 q_t^* + \lambda_1 q_t^* + \lambda_2 q_t^* + \delta_{01} w_{h,t} + \delta_{02} w_{h,t} + \delta_{10} q_t$$

$$+ \delta_{11} q_t + \delta_{12} q_t + \delta_{20} q_{b,t} + \delta_{21} q_{b,t} + \delta_{22} q_{b,t} + \delta_{30} q_{p,t} + \delta_{31} q_{p,t}$$

$$+ \delta_{32} q_{p,t} + \delta_{40} y_t + \delta_{41} y_t + \delta_{42} y_t + \delta_{50} w_t + \delta_{51} w_t + \delta_{52} w_t + \varsigma_t.$$  (4.25)

Subtracting $(\delta_{11} + \delta_{12})w_{h,t}$ from both sides of (4.25), combining terms, and rearranging yields

$$w_{h,t} = \frac{\delta_0}{1 - \delta_{01} - \delta_{02}} + \frac{\lambda_0 + \lambda_1 + \lambda_2 q_t^* + \delta_{10} + \delta_{11} + \delta_{12} q_t}{1 - \delta_{01} - \delta_{02}}$$

$$+ \frac{\delta_{20} + \delta_{21} + \delta_{22} q_{b,t} + \delta_{30} + \delta_{31} + \delta_{32} q_{p,t} + \delta_{40} + \delta_{41} + \delta_{42} y_t}{1 - \delta_{01} - \delta_{02}}$$

$$+ \frac{\delta_{50} + \delta_{51} + \delta_{52} w_t + \varsigma_t}{1 - \delta_{01} - \delta_{02}}.$$  (4.26)

where each coefficient gives the long-run impact on $w_{h,t}$ of a shock to the associated variable, ceteris paribus. It is clear from (4.24) and (4.26) that the long-run impact on $w_{h,t}$ of an
exogenous shock to a particular variable is proportional to the cumulation of the individual
effects of the shock that are transmitted through current and lagged values of the variable.

In order to incorporate short-run adjustments or disequilibrium effects into the model,
consider an alternative parameterization of (4.23). Subtracting \( w_{h,t-1} \) and adding and sub-
tracting \( \lambda_0 q_{t-1}^* - \lambda_0 q_{t-2}, \lambda_1 q_{t-2}, \delta_{10} q_{t-1}, \delta_{11} q_{t-2}, \delta_{20} q_{b,t-1}, \delta_{21} q_{b,t-2}, \delta_{30} q_{p,t-1}, \delta_{30} q_{p,t-2}, \delta_{31} q_{p,t-2}, \delta_{40} y_{t-1}, \delta_{40} y_{t-2}, \delta_{41} y_{t-2}, \delta_{50} w_{t-1}, \delta_{50} w_{t-2}, \delta_{51} w_{t-2}, \text{ and } (1 - \delta_{01} - \delta_{02}) w_{h,t-2} \)
from both sides of (4.23) and combining terms yields

\[
\Delta w_{h,t} = \delta_0 + \lambda_0 \Delta q_i^* + (\lambda_0 + \lambda_1) \Delta q_{t-1}^* + \delta_{10} \Delta q_i + (\delta_{10} + \delta_{11}) \Delta q_{t-1} + \\
+ \delta_{20} \Delta q_{b,t} + (\delta_{20} + \delta_{21}) \Delta q_{b,t-1} + \delta_{30} \Delta q_{p,t} + (\delta_{30} + \delta_{31}) \Delta q_{p,t-1} + \\
+ \delta_{40} \Delta y_{t-1} + (\delta_{40} + \delta_{41}) \Delta y_{t-1} + \delta_{50} \Delta w_t + (\delta_{50} + \delta_{51}) \Delta w_{t-1} - (1 - \delta_{01} - \delta_{02}) w_{h,t-2} + \\
+ (\lambda_0 + \lambda_1 + \lambda_2) q_{t-2}^* + (\delta_{10} + \delta_{11} + \delta_{12}) q_{t-2} + (\delta_{20} + \delta_{21} + \delta_{22}) q_{b,t-2} + \\
+ (\delta_{30} + \delta_{31} + \delta_{32}) q_{p,t} + (\delta_{40} + \delta_{41} + \delta_{42}) y_{t-2} + (\delta_{50} + \delta_{51} + \delta_{52}) w_{t-2} + \zeta_t,
\]
or writing it somewhat more compactly,

\[
\Delta w_{h,t} = \delta_0 + \lambda_0 \Delta q_i^* + (\lambda_0 + \lambda_1) \Delta q_{t-1}^* + \delta_{10} \Delta q_i + (\delta_{10} + \delta_{11}) \Delta q_{t-1} + \delta_{20} \Delta q_{b,t} + \\
+ (\delta_{20} + \delta_{21}) \Delta q_{b,t-1} + \delta_{30} \Delta q_{p,t} + (\delta_{30} + \delta_{31}) \Delta q_{p,t-1} + \delta_{40} \Delta y_{t-1} + \\
+ (\delta_{40} + \delta_{41}) \Delta y_{t-1} + \delta_{50} \Delta w_t + (\delta_{50} + \delta_{51}) \Delta w_{t-1} + \\
+ \alpha [w_{h,t-2} - \xi_1 q_{t-1} - \xi_2 q_{b,t-2} - \xi_3 q_{p,t-2} - \xi_4 y_{t-2} - \xi_5 w_{t-2}] + \zeta_t,
\]

where \( \alpha = -(1 - \delta_{01} - \delta_{02}), \lambda = (\lambda_0 + \lambda_1 + \lambda_2)/(1 - \delta_{01} - \delta_{02}), \xi_i = (\delta_{i0} + \delta_{i1} + \delta_{i2})/(1 - \delta_{01} - \delta_{02}) \) for \( i = 1, \ldots, 5 \), and \( \Delta \) is the first difference operator. The coefficients of the first differenced variables (i.e., \( \lambda_0, \delta_{10} \ldots \delta_{40} \)) give the short-run impacts on \( w_h \) of an exogenous
shock, whereas the coefficients of the lagged differenced variables are partial sums that give
the cumulative intermediate impacts.

If the long-run equilibrium can be written as \( y_{t-2} = \beta^\prime x_{t-2} \), then the bracketed term
in (4.27) can be written as \( [y_{t-2} - \beta^\prime x_{t-2}] \) and interpreted as an equilibrium error, and
Equation (4.27) is said to be written in error correction form. Equation (4.27) shows that the current change in \(w_{h,t}\) is a function both of current and lagged changes in the other variables in the model, \(\Delta x_i\) and \(\Delta x_{t-1}\), and the equilibrium error term in levels. The differenced variables capture the short-run dynamics and the variables in levels capture the long-run equilibrium. Because the stability condition \(|\delta| < 1\) ensures that \(\alpha < 0\), the current change in \(w_{h,t}\) is inversely related to the lagged equilibrium error. Each period past disequilibria are “corrected” at a rate equal to \(\alpha\) as market forces push \(w_h\) back towards its long-run equilibrium path. As a result, \(\alpha\) is interpreted as the speed of adjustment with which past equilibrium errors are corrected in succeeding periods.

In the more general case of \(k\) lags, \(k > 2\), the error correction model (ECM) of the industry derived demand relation can be written as

\[
\Delta w_{h,t} = \delta_0 + \sum_{j=1}^{k-1} \lambda_j^* \Delta q_{t-j}^* + \sum_{j=0}^{k-1} \delta_{0j}^* \Delta w_{h,t-j} + \sum_{j=0}^{k-1} \delta_{1j}^* \Delta q_{t-j}^* + \sum_{j=0}^{k-1} \delta_{2j}^* \Delta q_{b,t-j}^* + \sum_{j=0}^{k-1} \delta_{3j}^* \Delta q_{p,t-j}^* + \sum_{j=0}^{k-1} \delta_{4j}^* \Delta y_{t-j}^* + \sum_{j=0}^{k-1} \delta_{5j}^* \Delta w_{t-j}^* + \alpha \left[ w_{h,t-k} - \Lambda q_{t-k}^* - \xi_1 q_{t-k} - \xi_2 q_{b,t-k} - \xi_3 q_{p,t-k} - \xi_4 y_{t-k} - \xi_5 w_{t-k} \right] + \zeta_t,
\]

where \(\lambda_0^* = \lambda_0\) gives the short-run estimate of oligopsony power, and where

\[
\lambda_j^* = \sum_{l=0}^{j} \lambda_l, \quad \Lambda = -\frac{1}{\alpha} \sum_{l=0}^{k} \lambda_l, \quad \delta_{0j}^* = \sum_{l=1}^{j} \delta_{0l}, \quad \delta_{ij}^* = \sum_{l=0}^{j} \delta_{il}, \quad \xi_i = -\frac{1}{\alpha} \sum_{l=0}^{k} \delta_{il}, \quad \alpha = -\left(1 - \sum_{l=1}^{k} \delta_{0l}\right)
\]

are, defined as follows: (a) \(\lambda_j^*, j = 1 \ldots k-1\) are partial sums giving the intermediate-run effects of oligopsony power; (b) \(\Lambda\) is the long-run estimate of oligopsony power; (c) \(\delta_{0j}^*\) are partial sums giving the intermediate-run effects of \(w_h\); (d) \(\delta_{ij}^*\) are partial sums giving the short- and intermediate-run effects of the other variables in the model; (e) \(\xi_i\) are partial

\[49\]In (4.27) \(y_{t-2} = w_{h,t-2}, \beta' = (\Lambda, \xi_1, \ldots, \xi_5)\), and \(x_{t-2} = (q_{r,t-2}, q_{b,t-2}, q_{p,t-2}, y_{t-2}, w_{t-2})\).
sums giving the long-run effects of the other variables; and (f) $\alpha$ is the speed of adjustment parameter.\textsuperscript{50}

\textsuperscript{50}For the case of $k = 2$, it is instructive to compare (4.27) and (4.28) to see how the parameters in the ARDL and error correction specifications relate to each other.
In this section we provide a brief overview of selected topics from the time series econometrics literature. In particular, we focus on stationary and nonstationary time series, the spurious regression problem, tests for unit roots and cointegration, and how these concepts relate to error correction modeling.\textsuperscript{51}

Much of econometric theory assumes that the joint probability distribution of the data, the data generating process (DGP), is stationary. A stochastic process, of which a time series is a single realization, is stationary if its distribution is independent of time. In most cases this assumption is too strong, and a weaker form of stationarity suffices. A stochastic process is weakly or covariance stationary if its distribution has a constant mean and variance and the autocovariances depend only on the distance in time between observations. A variable is nonstationary if any one or more of these conditions is violated.\textsuperscript{52} The distinction between a stationary and nonstationary time series is crucial for valid statistical inference.

A characteristic common of most economic data is the presence of trends. A time series with a trend is nonstationary by definition because the mean of the series is a function of

\textsuperscript{51}See Hamilton (1994) for a detailed exposition of the issues discussed in this section.

\textsuperscript{52}The concern here is with nonstationarity in the mean.
time. A trend can be deterministic, stochastic, or a mixture of the two, and the type of trend dictates the appropriate stationary transformation.

A series that has a deterministic trend is said to be trend stationary, i.e., the series fluctuates as a result of random shocks about a deterministic trend. However, the effect of the shocks eventually dies out and the series returns to its trend path. Such a variable can be rendered stationary by regressing it on a deterministic time trend, in which case statistical inference follows standard asymptotic theory.

A time series contains a stochastic trend if it wanders randomly with no tendency to return to a fixed value or trend path. The erratic movement in the series gives rise to the term “random walk” that is used to describe variables containing a stochastic trend. The randomness in the series arises from the cumulation or sum of past shocks. The summation of shocks is analogous to the concept of a definite integral in calculus, hence a variable with a stochastic trend is said to be integrated. Unlike a trend stationary series, shocks persist indefinitely and have a permanent effect on the evolution of an integrated series. In most cases, a stochastic trend can be removed by taking the first difference of an integrated variable. Generally, a variable is said to be integrated of order $d$—written $I(d)$—if its $d$th difference is stationary. For example, an $I(0)$ variable is stationary, whereas an $I(1)$ variable is nonstationary, integrated of order one, or difference stationary. Most economic variables are integrated of order no higher than 2, with the majority being $I(1)$.

In order to illustrate the distinction between $I(0)$ and $I(1)$ variables, consider the specification given by

$$y_t = \rho y_{t-1} + \varepsilon_t,$$

(5.1)

---

53 A random walk is actually a special case of a stochastic trend (see Charemza and Deadman 1997, pp. 89–91).
where $\varepsilon \sim iid(0, \sigma^2_\varepsilon)$. The series $y_t$ is stationary if $|\rho| < 1$. Alternatively, when $\rho = 1$ equation (5.1) is said to contain a unit root and an equivalent expression is given by

$$\Delta y_t = \varepsilon_t,$$

where $\Delta$ denotes the first difference operator.\(^{54}\) Equation (5.1) is an example of a pure random walk or a random walk without drift. Note that the terms stochastic trend, random walk, difference stationary, and unit root are equivalent ways of characterizing the persistence of shocks in a time series.

There are important reasons for distinguishing between deterministic and stochastic trends. Plosser and Schwert (1977) showed that differencing a variable to remove a deterministic trend induces a moving average unit root in the errors. Alternatively, Nelson and Kang (1981, 1984) showed that regressing a difference stationary time series on a time trend to remove a unit root induces spurious periodic behavior in the errors. But perhaps the most important reason for distinguishing between trend and difference stationarity is that a difference stationary series has a nonstandard distribution, with obvious implications for statistical inference.

Traditionally, decisions on whether to difference nonstationary variables were based on the shape of the autocorrelation and partial autocorrelation functions (Box and Jenkins 1976). An alternative to the Box-Jenkins method is formal parametric tests for a unit root in the autoregressive representation of a time series first developed by Dickey and Fuller (1979, 1981). Since their publication, these articles have served as a wellspring of theoretical and empirical research on formal parametric and nonparametric tests for unit roots.\(^{55}\)

\(^{54}\)The case in which $\rho > 1$ is not considered because it implies explosive behavior, something atypical of most economic time series.

\(^{55}\)See Maddala and Kim (1998) and for a recent survey of the unit root literature.
In the Dickey-Fuller testing framework it is more convenient to rewrite equation (5.1) as
\[ \Delta y_t = \theta y_{t-1} + \sum_{i=1}^{k} \Delta y_{t-i} + \varepsilon_t, \]  
(5.2)
where \( \theta = \rho - 1 \), and where (5.2) is obtained by subtracting \( y_{t-1} \) from both sides of (5.1). Equation (5.2) is augmented with lags of the dependent variable to account for any residual autocorrelation and as such is referred to as the augmented Dickey-Fuller (ADF) regression. The Dickey-Fuller procedure tests the null hypothesis \( H_0 : \rho = 1 \) against the alternative hypothesis \( H_1 : \rho < 1 \), which is equivalent to a test of \( H_0 : \theta = 0 \) against the alternative hypothesis \( H_1 : \theta < 0 \) in equation (5.2).\(^{56}\) Decisions about unit roots are based on a \( t \)-test of \( H_0 \), though the test statistic has a nonstandard distribution under the null. The so-called Dickey-Fuller distribution does not have a closed form solution, and critical values must be obtained using simulation methods.\(^{57}\) Despite their popularity, unit root tests have poor power properties, especially when \( \rho \) in equation (5.1) is less than but close to one (Agiakloglou and Newbold 1992).\(^{58}\) To mitigate this problem, Elliott et al. (1996) have developed a modified Dickey-Fuller test with better power properties.

Another reason to be concerned about the presence of stochastic trends is that the results from a regression of one \( I(1) \) variable on another may be spurious. A spurious regression is one in which two or more unrelated \( I(1) \) variables appear to be related solely because each

---

\(^{56}\)Stationarity tests reverse the roles of the null and alternative hypotheses, and thus complement conventional unit root tests. Since taking the first difference of a stationary series induces a moving average (MA) unit root, stationarity tests are equivalent to tests for an MA unit root in a time series. The standard reference is Kwiatkowski et al. (1992).

\(^{57}\)Critical values can be found in Fuller (1976), Cheung and Lai (1995), and MacKinnon (1996) inter alia.

\(^{58}\)Cochrane (1991) points out that most statistical tests have low power against local alternatives. In most cases this inability to discriminate between competing hypotheses does not pose a significant inferential problem. However, the same cannot be said for unit root tests given the radically different implications for inference under the null and alternative hypotheses.
variable exhibits trending behavior (see Granger and Newbold 1974; Phillips 1986). An empirical example of a spurious regression is provided in Hendry (1980), who regressed the U.K. consumer price index on cumulative rainfall in the U.K. and found a statistically significant relationship between the variables. Typical symptoms of a spurious regression include statistically significant coefficients, a high $R^2$, and autocorrelated residuals. Possible cures for the spurious regression problem include (i) adding lagged dependent and independent variables as regressors, (ii) estimating the equation in first differences, or (iii) estimating the equation using generalized least squares (Hamilton 1994, pp. 561–2).

The relevance of unit roots to our model stems from the fact that the error correction specification contains levels and differences of variables in the same equation. If all variables in (4.28) are $I(1)$, their first differences are stationary. However, the bracketed term is a linear combination of $I(1)$ variables and in general such a combination will also be $I(1)$. In this case equation (4.28) represents an unbalanced regression of an $I(0)$ variable on an $I(1)$ variable, a situation that complicates both inference and interpretation of results (Banerjee et al. 1993, pp. 164–8). However, if the bracketed term in (4.28) is stationary, the variables are said to be cointegrated. In this case the equation is balanced statistically, i.e., both the left- and righthand sides are $I(0)$, standard asymptotic inference applies, and interpretation is straightforward.

A set of $I(1)$ variables is cointegrated if a linear combination of these variables is stationary or $I(0)$ (Engle and Granger 1987). More generally, a set of $I(d)$ variables is cointegrated if a linear combination of the variables is $I(b)$, where $b < d$. The foregoing discussion points to a relationship between error correction and cointegration, and, indeed, Engle and Granger prove a representation theorem which asserts that a set of $I(1)$ vari-
ables has an error correction representation if and only if the variables are cointegrated.\textsuperscript{59} As is true for unit roots, formal statistical tests exist to help determine whether a set of variables is cointegrated. Two popular tests are those developed by Engle and Granger, and Johansen (1988, 1991). Engle and Granger use a single-equation method that tests the null of no cointegration using an ADF test of the residuals from a cointegrating regression. Johansen uses a systems-based vector autoregressive (VAR) modeling approach to estimate the cointegrating space, i.e., the number of cointegrating relationships. We will have more to say about these cointegration tests in chapter 7.

\textsuperscript{59}An advantage to working with cointegrated variables is that the ordinary least squares (OLS) estimator is super-consistent, i.e., the OLS estimates converge to their true values at rate $T$—where $T$ is the sample size—as opposed to the standard rate of $T^{1/2}$ (Stock 1987).
CHAPTER 6

THE DATA

The raw data consists of seasonally unadjusted monthly observations on pork production, federally inspected production of beef and poultry, average live weight and the average price of barrows and gilts, per capita personal disposable income, and the hourly wage of production workers in meat packing plants for the period from January 1988 to December 2000. Data was aggregated to the quarterly frequency by taking sums of the quantity variables and averages of the economic variables.\(^{60}\) Although aggregation results in a loss of information, Holt and Johnson (1988, p. 314) write that “many production stages in the hog industry occur naturally within [the quarterly] interval.” Summary statistics are presented in table 6.1 on the following page, and the logarithms of the data are graphed in figure 6.1 on page 55. The graphs reveal that several of the variables exhibit either one or both of seasonal movements and trending behavior. An outlier is also evident in the hog price series.\(^{61}\)

The data were collected from a variety of sources. Pork production was calculated as the product of slaughter and average live weight of federally inspected barrows and

\(^{60}\)The first through fourth quarters correspond to the hog marketing year which runs from December 1 to November 30. The quarters are defined as follows: (I) December-February, (II) March-May, (III) June-August, and (IV) September-November.

\(^{61}\)The combination of record hog production, record imports of Canadian hogs, limited capacity in packing plants, large stocks of pork in cold storage, and falling export demand due to the Asian financial crisis resulted in real hog prices falling to record lows in the fourth quarter of 1998 (see Luby 1999).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units$^b$</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pork production ($q$)</td>
<td>mill. lbs.</td>
<td>8.269</td>
<td>0.103</td>
<td>8.048</td>
<td>8.453</td>
</tr>
<tr>
<td>Beef production ($q_b$)</td>
<td>mill. lbs.</td>
<td>8.693</td>
<td>0.074</td>
<td>8.561</td>
<td>8.843</td>
</tr>
<tr>
<td>Poultry production ($q_p$)</td>
<td>mill. lbs.</td>
<td>8.871</td>
<td>0.185</td>
<td>8.501</td>
<td>9.150</td>
</tr>
<tr>
<td>Live weight ($bgwt)^c$</td>
<td>pounds</td>
<td>5.192</td>
<td>0.031</td>
<td>5.138</td>
<td>5.254</td>
</tr>
<tr>
<td>Real hog price ($w_h$)</td>
<td>$/cwt.$</td>
<td>3.442</td>
<td>0.218</td>
<td>2.704</td>
<td>3.837</td>
</tr>
<tr>
<td>Real income ($y$)</td>
<td>$/annum$</td>
<td>9.516</td>
<td>0.043</td>
<td>9.458</td>
<td>9.600</td>
</tr>
<tr>
<td>Real wage ($w$)</td>
<td>$/hour$</td>
<td>1.874</td>
<td>0.042</td>
<td>1.824</td>
<td>1.987</td>
</tr>
<tr>
<td>Int. term ($w_h \cdot pglit)^e$</td>
<td>—</td>
<td>7.259</td>
<td>0.402</td>
<td>5.836</td>
<td>7.930</td>
</tr>
<tr>
<td>Pigs per litter ($pglit$)</td>
<td>—</td>
<td>2.111</td>
<td>0.047</td>
<td>2.031</td>
<td>2.182</td>
</tr>
</tbody>
</table>

$^a$ Logarithms of data  
$^b$ Units correspond to the levels of the data  
$^c$ Average live weight, barrows & gilts  
$^d$ Dollars per hundredweight  
$^e$ Supply interaction term

gilts. Data on slaughter, average live weight, and federally inspected production of beef was obtained from the USDA-NASS Published Estimates Database. Data on federally inspected production of poultry came from the Poultry Yearbook published by USDA-ERS.

Hog prices are for the Iowa-Southern Minnesota direct market and were obtained from the Des Moines, Iowa office of USDA-AMS.\textsuperscript{62} Prices are for U.S. grade 1–3 barrows and gilts in the 240–250 lb. (1988–1991) and 230–250 lb. (1992–1998) weight classes. In January 1999 USDA-AMS began reporting hog prices on a carcass merit basis exclusively. As a result of this change, data for 1999–2000 are closing market weighted average prices for a 49–51% lean, plant-delivered, base market hog.

Income is per capita personal disposable income published by the U.S. Department of Commerce, Bureau of Economic Analysis (BEA). The packing plant wage is average

\textsuperscript{62}Previous research supports using the Iowa-Southern Minnesota price as a representative price for the entire U.S. market. As discussed in section 2.1 (note 9), Schroeder and Mintert (1999) point out that the Iowa-Southern Minnesota price is used as a base price in many formula price contracts. Furthermore, empirical analysis conducted by USDA-GIPSA (1996, p. 48) found that regional spot markets constituted a “single U.S. market.”
hourly earnings of production workers employed in meat packing plants (SIC 2011) published by the U.S. Department of Labor, Bureau of Labor Statistics (BLS). Finally, the economic variables were deflated by the U.S. city average of the consumer price index (CPI) for all items and all urban consumers (1982–84=100) published by BLS.
CHAPTER 7

EMPIRICAL RESULTS

In this chapter we present and discuss the empirical results of the model developed in chapter 4. We start with the supply equation. We then move on to a discussion of the demand relation and short- and long-run indices of oligopsony power. However, because the demand relation is specified in error correction form, we first present results of tests for unit roots and cointegration to ensure the validity of the error correction specification. The estimable forms of the supply equation and demand relation were chosen based on the results of a general-to-specific econometric modeling strategy advocated by Hendry (1995).\(^{63}\) Estimation was done using version 10.0 of PcGive by Hendry and Doornik (2001) and version 7.0 of Stata.

7.1 Supply

The model of hog supply is given by equation (4.21), which is reproduced here for convenience:

\[
q_t = A(1)pc_t + B(1)w_{ht} + \varphi \{w_{ht} \cdot pglit_t\} + \sum_{i=1}^{3} \pi_i S_{i,t} + \delta t + \eta_t. \tag{4.21}
\]

\(^{63}\)The general-to-specific (GS) approach starts with an overparameterized model and uses statistical tests to arrive at a more parsimonious specification. See Gilbert (1986) for an accessible discussion.
Recall from the discussion in section 4.2 that the slope of the long-run supply curve is given by $B(1) + \varphi \cdot pg_{lit}$. The interaction term in (4.21) provides the rotation of the supply curve necessary to identify oligopsony power. As previously discussed, we assume that the supply curve rotates with technical change, and we use pigs per litter rather than time as a proxy for this change. The pigs per litter series is graphed in figure 7.1.\(^{64}\) The graph shows a clear upward trend in pigs per litter over the sample period reflecting improvements in genetics, pharmaceuticals, and production methods.

Equation (4.21) was estimated using the two-stage least squares estimator to account for endogeneity of both the contemporaneous hog price and interaction term.\(^{65}\) In contrast to the results reported by Holt and Johnson (1988), our results (not reported) yielded

\(^{64}\)It should be noted that the upward trend in figure 7.1 reflects technological change and the fact that less efficient producers have exited the industry.

\(^{65}\)The interaction term is endogenous in (4.21) since it is a function of the contemporaneous hog price.
a downward sloping long-run hog supply curve, a finding that implies hog producers are better off if spot hog markets are monopsonistic or oligopsonistic. As mentioned in section 4.2, Holt and Johnson developed a seven equation model of hog supply response, and the complexity of their model points to a misspecification in our simplified version. Holt and Johnson (op. cit., p. 314) write that “hog production occurs sequentially with different functions being performed at each stage or sequence in the production process.” In point of fact, Holt and Johnson do not estimate an equation like (4.21). Rather, they estimate separate equations for barrow and gilt slaughter (4.11) and average live weight (4.12). Equation (4.15) showed that the slope of the long-run hog supply curve is a function of parameters in (4.12). Consequently, we focus on specification and estimation of the live weight equation, using the estimated parameters to calculate the slope of the long-run hog supply curve.

Allowing for a constant, seasonal dummies, a time trend, and lagged dependent variables to account for any autocorrelation in the residuals results in the general specification given by

\[
bgwt_t = \mu + B(L)w_{h,t} + \varphi \{w_{h,t} \cdot pglit_t\} + \Gamma(L)bgwt_t + \sum_{i=1}^{3} \pi_i S_i + \delta t + \epsilon_t, \tag{7.1}
\]

where \(B(L)\) and \(\Gamma(L)\) are polynomials in the lag operator of orders to be determined. Because farmer decisions as to the time hogs are marketed—and by extension the average weight of hogs—is largely a function of prevailing market conditions, the barrow and gilt price is deemed exogenous in (7.1). As a result, the ordinary least squares (OLS) estimator is consistent, assuming of course the model is not misspecified.
Starting with five lags each of $w_h$ and $bgwt$ to allow for multiplicative seasonal effects, and using a general-to-specific testing strategy, we obtained the following specification:

$$bgwt_t = \mu + \sum_{i=0}^{1} \beta_i w_{h,t-i} + \varphi \{w_{h,t} \cdot pglit_t\} + \sum_{j=1}^{2} \gamma_j bgwt_{t-j} + \sum_{k=1}^{3} S_k + \delta t + \epsilon_t, \quad (7.2)$$

where all variables are defined as before. Model reduction proceeded on the basis of sequential $t$-tests discussed in Ng and Perron (1995). The lags of the dependent variable account for autocorrelation in the residuals.

The lags of the dependent variable account for autocorrelation in the residuals. Model reduction proceeded on the basis of sequential $t$-tests discussed in Ng and Perron (1995). The lags of the dependent variable account for autocorrelation in the residuals.

The results are reported in table 7.1 on the next page. Overall, they indicate that the model fits the data well; five of the variables are significant at the 1% level, and another two are significant at the 10% level, though the economic significance of most variables is small. The estimated long-run own-price elasticity points to a highly inelastic supply curve. Thus, these results suggest that even a small monopsonistic or oligopsonistic restriction of hog purchases by pork packing firms should induce large declines in hog prices. Holt and Johnson (1988) found a negative short-run response of average weights to changes in hog prices. However, the interaction term in (7.2) means that $\beta_0$ cannot be interpreted as the short-run price response.

A series of misspecification tests were employed as a check on the validity of equation (7.2). The results of Lagrange multiplier tests for serial correlation and autoregressive conditional heteroskedasticity (ARCH) of various orders in the residuals are reported in

---

66 The Ng-Perron procedure iteratively tests and eliminates the highest lag, stopping when the $p$-value is less than a chosen level of significance, in this case 10 percent.

67 Note that equation (7.2) was also estimated with a dummy variable to account for the record decline in real hog prices that occurred in the fourth quarter of 1998 (see note 61). The dummy variable takes the value −1 in 1998.IV and 0 otherwise. The coefficient was neither statistically nor economically significant and hence was excluded from the final specification.

68 Recall that because we use a double-log specification, the parameter estimates for the variables listed in table 7.1 are estimated elasticities, whereas the coefficients on the constant, seasonal dummies, and the time trend are estimated percentage changes.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Estimate</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$\mu$</td>
<td>2.917</td>
<td>4.275***</td>
</tr>
<tr>
<td>$S1$</td>
<td>$\pi_1$</td>
<td>0.004</td>
<td>0.939</td>
</tr>
<tr>
<td>$S2$</td>
<td>$\pi_2$</td>
<td>-0.001</td>
<td>-0.129</td>
</tr>
<tr>
<td>$S3$</td>
<td>$\pi_3$</td>
<td>-0.015</td>
<td>-4.580***</td>
</tr>
<tr>
<td>$t$</td>
<td>$\delta$</td>
<td>0.002</td>
<td>4.015***</td>
</tr>
<tr>
<td>$w_{ht}$</td>
<td>$\beta_0$</td>
<td>0.102</td>
<td>1.800*</td>
</tr>
<tr>
<td>$w_{ht-1}$</td>
<td>$\beta_1$</td>
<td>0.020</td>
<td>2.932***</td>
</tr>
<tr>
<td>$w_{ht} \cdot plit_t$</td>
<td>$\varphi$</td>
<td>-0.052</td>
<td>-1.971*</td>
</tr>
<tr>
<td>$bgwt_t$</td>
<td>$\gamma_1$</td>
<td>0.586</td>
<td>4.056***</td>
</tr>
<tr>
<td>$bgwt_{t-2}$</td>
<td>$\gamma_2$</td>
<td>-0.206</td>
<td>-1.353</td>
</tr>
<tr>
<td>LR slopea</td>
<td>$B(1) + \varphi \cdot plit_t$</td>
<td>0.019</td>
<td>3.462***b</td>
</tr>
</tbody>
</table>

1, 5, and 10% sig. levels denoted by ****, ***, and *.  
$T = 50; R^2 = 0.984; F_{9,40} = 270.514^{***}$  
a Hog supply curve; $B(1) = \beta_0 + \beta_1$; long-run slope  
calculated at the mean of plit.  
b Asymptotic standard error calculated using a first-order Taylor series approximation.

Table 7.1–Estimation results for (7.2)

Table 7.2 on the following page. Both test statistics have a $\chi^2(p)$ distribution. The LM test results indicate that mild fourth-order autocorrelation might be a problem. However, an overall $F$-test of autocorrelation up to the fourth order yields a test statistic of 1.634 with a $p$-value of 0.187. Results of the ARCH tests indicate that autoregressive conditional heteroskedasticity is not a problem in our model. Conventional Breusch-Pagan and White tests for conditional heteroskedasticity also show no evidence of misspecification. The Breusch-Pagan test is based on a regression of the squared residuals on the original

---

69 The validity of Lagrange multiplier tests rests on the assumption that the residuals are homoskedastic. If this assumption is violated, then robust test statistics should be used (Wooldridge 1991). However, tests for heteroskedasticity in turn depend on the absence of serial correlation in the residuals. Wooldridge (2000) suggests first testing for autocorrelation, using a robust test statistic if heteroskedasticity is suspected.

70 The $F$-statistic has better small sample properties than the $\chi^2$ version of the test (Hendry and Doornik 2001, p. 260).
regressors. The White test is based on a regression of the squared residuals on the original regressors, their squares, and cross-products. In each case the test statistic equals $TR^2$ and has a $\chi^2$ distribution, where $k$ is the number of regressors (excluding the constant). The calculated value of the Breusch-Pagan statistic is 12.975 with a $p$-value of 0.164, and that for the White test is 34.407 with a $p$-value of 0.679.

A formal test due to Hausman (1978) permits testing the assumption that the hog price is exogenous in (7.2). The Hausman procedure consists of estimating the reduced form regression for $w_h$ and using the residuals from this estimation as an additional explanatory variable in (7.2). A $t$-statistic is then used to test the null hypothesis that the coefficient of the added regressor equals zero. A rejection of the null provides evidence of endogeneity.

In conducting the Hausman test, the reduced-form residuals were obtained by regressing $w_h$ on all other righthand side variables in (7.2) in addition to $q_b, q_p, y$, and $w$ from the demand relation (4.28). We calculated a test statistic of $-1.499$ with a $p$-value of 0.147, indicating that the hog price is exogenous for average live weight.

As a final check on our model, we used the regression specification error test (RESET) developed by Ramsey (1969) as a general test of functional form. The testing procedure involves adding higher powers of the OLS fitted values as regressors to (7.2). A $t$- or $F$-

---

**Table 7.2–Misspecification tests**

<table>
<thead>
<tr>
<th>Test</th>
<th>Order ($p$)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>LM($p$)</td>
<td>1.256</td>
<td>1.593</td>
<td>7.682</td>
</tr>
<tr>
<td></td>
<td>(0.262)</td>
<td>(0.451)</td>
<td>(0.104)</td>
</tr>
<tr>
<td>ARCH($p$)</td>
<td>0.358</td>
<td>1.517</td>
<td>2.467</td>
</tr>
<tr>
<td></td>
<td>(0.550)</td>
<td>(0.488)</td>
<td>(0.650)</td>
</tr>
</tbody>
</table>

See Verbeek (2000, pp. 95, 266)

$p$-values in parentheses
statistic is used to test the null hypothesis that the coefficients on the added regressors are zero. We added a squared term to (7.2) and calculated a $t$-statistic of 1.842 with a $p$-value of 0.073. Thus, the RESET test shows no evidence of functional form misspecification at the 5% level, though it does reject at the 10% level. On the basis of the overall test results, we conclude that our model represents a reasonable specification of hog supply.

7.2 Demand

Before estimating the demand relation, we must determine whether a long-run equilibrium relationship exists between the variables in the model. Recall from the discussion in chapter 5 that if the levels of the variables in equation (4.28) have a unit root, then their first differences are stationary. Furthermore, if a linear combination of the $I(1)$ variables cointegrate, then the bracketed term in (4.28) is also stationary and the error correction model represents a valid specification.

7.2.1 Unit Root Tests

Figure 6.1 on page 55 shows that several of the series exhibit marked seasonality. Like trending behavior in a nonseasonal series, seasonality can be either deterministic, stochastic, or a combination of the two. The type of seasonality dictates the appropriate stationary transformation. Deterministic seasonality is modeled using seasonal dummy variables that take the value 1 in season $s = 1 \ldots S$ and 0 otherwise.\footnote{Here $S$ denotes the periodicity of the data, e.g., 4 for quarterly data and 12 for monthly data.} A series exhibits stochastic seasonality, or is said to have a seasonal unit root, if seasonal shocks persist indefinitely. Stochastic seasonality requires seasonal differencing to induce stationarity (see below). Assuming the absence of deterministic elements such as a constant or trend, a formal representation of a
series with a seasonal unit root is given by

$$\Delta_s y_t = \varepsilon_t, \quad (7.3)$$

where $\Delta_s$ is the seasonal differencing operator, $s$ indexes the periodicity of the data, and $\varepsilon \sim iid(0, \sigma^2_{\varepsilon})$.

For the case of a quarterly time series, the seasonal differencing operator can be factored as

$$\Delta_4 = 1 - L^4 = (1 - L)(1 + L + L^2 + L^3) \quad (7.4a)$$

$$= (1 - L)(1 + L)(1 - iL)(1 + iL) \quad (7.4b)$$

where $i = \sqrt{-1}$. The filter $(1 + L + L^2 + L^3)$ in (7.4a) is the seasonal summation operator and removes all seasonal unit roots in a time series, though it does not remove a nonseasonal unit root. The unit roots $1, -1, \text{ and } \pm i$ in (7.4b) correspond to the annual (nonseasonal), semiannual, and quarterly frequencies. Equation (7.4b) implies that a series can have unit roots at each of the three frequencies. A formal parametric test of seasonal unit roots in a quarterly time series is the so-called HEGY test developed by Hylleberg et al. (1990). The HEGY test derives from the factorization in (7.4b) and is based on the auxiliary regression

$$\Delta_4 y_t = \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \varepsilon_t, \quad (7.5)$$

where

$$y_{1,t} = (1 + L + L^2 + L^3) y_t$$
$$y_{2,t} = -(1 - L + L^2 - L^3) y_t$$
$$y_{3,t} = -(1 - L^2) y_t.$$

72 The seasonal differencing operator is defined by $\Delta_s y_t = y_t - y_{t-s}$. Alternatively, we can use lag operator notation and write the seasonal difference as $\Delta_s = 1 - L^s$.

73 Nonseasonal unit roots were discussed in chapter 5.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Lags</th>
<th>T</th>
<th>Test Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pork production ((q))</td>
<td>3</td>
<td>44</td>
<td>6.82**</td>
</tr>
<tr>
<td>Beef production ((q_b))</td>
<td>0</td>
<td>47</td>
<td>9.64***</td>
</tr>
<tr>
<td>Poultry production ((q_p))</td>
<td>0</td>
<td>47</td>
<td>13.30***</td>
</tr>
<tr>
<td>Real hog price ((w_h))</td>
<td>2,4</td>
<td>43</td>
<td>16.30***</td>
</tr>
<tr>
<td>Real income ((y))</td>
<td>0</td>
<td>47</td>
<td>13.14***</td>
</tr>
<tr>
<td>Real wage ((w))^a</td>
<td>2</td>
<td>45</td>
<td>14.95***</td>
</tr>
<tr>
<td>Oligopsony wedge ((q^*)^b)</td>
<td>0</td>
<td>47</td>
<td>10.09***</td>
</tr>
</tbody>
</table>

Critical values from Franses and Hobijn (1997); auxiliary regressions include a constant and seasonal dummies unless stated otherwise; lag length chosen using a sequential t-test at a 10% significance level with nonsignificant intermediate lags deleted; 1, 5, and 10% sig. levels denoted by ***, **, and *.

^a Regression includes a constant, seasonal dummies, and a trend
^b \(q^* = -q_{\frac{1}{4}} - q_{\frac{1}{2}} - \gamma_{\frac{3}{4}} \cdot \text{pglit} \), where the parameters are from (7.2).

Table 7.3–HEGY test of \(\Delta \Delta_4\) filter

If \(\pi_1 = 0\), the series has a nonseasonal unit root (stochastic trend). If \(\pi_2 = 0\), the series has a unit root at the semiannual frequency. If \(\pi_3 = \pi_4 = 0\), the series as a unit root at the quarterly frequency.

Working with airline passenger data, Box and Jenkins (1976) found that both first and seasonal differences \(\Delta \Delta_4\) were necessary to induce stationarity in the series. The so-called “airline model” has since been found to be an adequate representation for many seasonal time series. Consequently, we tested the airline model by applying the HEGY test to the first difference of each variable in the demand relation. The results of these tests are reported in table 7.3. We report two \(F\)-statistics (see Ghysels et al. 1994) and a \(t\)-statistic corresponding to a conventional Dickey-Fuller test. The \(F_{1.4}\) and \(F_{2.4}\) statistics test the hypotheses \(H_0: \pi_1 = \cdots = \pi_4 = 0\) and \(H_0: \pi_2 = \cdots = \pi_4 = 0\). The \(t\)-statistic tests \(H_0: \pi_1 = 0\). The results provide strong evidence to reject the null hypotheses at the
seasonal and nonseasonal frequencies. The only non-rejection occurs for $q$ with the $F_{2.4}$ statistic, indicating that the series should be transformed using the seasonal summation operator. However, given that the other test statistics reject the null, we feel comfortable in rejecting stochastic seasonality for this series. Thus, we conclude that the first difference of each of the variables does not contain a seasonal unit root.

We next tested for the presence of a seasonal unit root in the levels of the variables. Test results are reported in table 7.4. Again, the $F$-statistics strongly reject the null of stochastic seasonality in all series. Thus, it appears reasonable to model seasonality in these series as deterministic. However, note that the $t$-statistic rejects $H_0: \pi_1 = 0$ for $q$, $w_h$, and the interaction term, indicating that these variables are stationary in levels. We investigate this possibility further using nonseasonal unit root tests.

The graph of $w_h$ in figure 6.1 on page 55 indicates a possible outlier in late 1998. It is known that outliers induce “in the errors a moving-average (MA) component with a neg-

<table>
<thead>
<tr>
<th>Variable</th>
<th>Lags</th>
<th>$T$</th>
<th>$F_{1.4}$</th>
<th>$F_{2.4}$</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pork production ($q$)</td>
<td>1</td>
<td>47</td>
<td>12.87**</td>
<td>9.56***</td>
<td>-4.46***</td>
</tr>
<tr>
<td>Beef production ($q_b$)</td>
<td>0</td>
<td>48</td>
<td>23.27***</td>
<td>26.09***</td>
<td>-2.49</td>
</tr>
<tr>
<td>Poultry production ($q_p$)</td>
<td>2</td>
<td>46</td>
<td>9.81***</td>
<td>9.70***</td>
<td>-2.08</td>
</tr>
<tr>
<td>Real hog price ($w_h$)</td>
<td>0</td>
<td>48</td>
<td>83.95***</td>
<td>110.25***</td>
<td>-4.77***</td>
</tr>
<tr>
<td>Real income ($y$)</td>
<td>0</td>
<td>48</td>
<td>49.13***</td>
<td>65.46***</td>
<td>-1.57</td>
</tr>
<tr>
<td>Real wage ($w$)</td>
<td>0</td>
<td>48</td>
<td>40.40***</td>
<td>47.68***</td>
<td>-1.83</td>
</tr>
<tr>
<td>Oligopsony wedge ($q^*$)$^a$</td>
<td>0</td>
<td>48</td>
<td>16.13***</td>
<td>21.30***</td>
<td>-1.59</td>
</tr>
</tbody>
</table>

Critical values from Franses and Hobijn (1997); auxiliary regressions include a constant, seasonal dummies, and a trend; lag length chosen using a sequential t-test at a 10% significance level; 1, 5, and 10% sig. levels denoted by ***, **, and *. $^a q^* = -q_{1-\gamma_1-\gamma_2}\frac{1-p_0+p_1+p_2}{p_0+p_1+p_2+p_3}$, where the parameters are from (7.2)

Table 7.4–HEGY test of $\Delta_4$ filter
Table 7.5–Dickey-Fuller Unit Root Test with Additive Outliers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Test Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I(2)^b$</td>
</tr>
<tr>
<td>Pork production ($q$)</td>
<td>$-4.465^{**}$</td>
</tr>
<tr>
<td>Beef production ($q_b$)</td>
<td>$-5.737^{***}$</td>
</tr>
<tr>
<td>Poultry production ($q_p$)</td>
<td>$-5.026^{***d}$</td>
</tr>
<tr>
<td>Real hog price ($w_h$)</td>
<td>$-3.301^{***c}$</td>
</tr>
<tr>
<td>Real income ($y$)</td>
<td>$-4.402^{***}$</td>
</tr>
<tr>
<td>Real wage ($w$)</td>
<td>$-3.588^{***}$</td>
</tr>
<tr>
<td>Oligopsony wedge ($q^*$)</td>
<td>$-8.218^{***}$</td>
</tr>
</tbody>
</table>

Critical values obtained from Cheung and Lai (1995); 1, 5, and 10% sig. levels denoted by $^{***}$, $^{**}$, and $^*$

\[ q^* = -q \frac{(1-\gamma_1-\gamma_2)}{\phi_0+\phi_1+\phi_2+ \phi_3}, \]

where the parameters are from (7.2)

\[ a \] Constant, no trend unless indicated otherwise
\[ b \] Constant and trend
\[ c \] Outliers detected at 1989.II and 1991.II
\[ d \] Outlier detected at 1999.I
\[ e \] Outlier detected at 1998.IV
\[ f \] Outlier detected at 1990.IV
\[ g \] Outlier detected at 1998.IV

Table 7.5–Dickey-Fuller Unit Root Test with Additive Outliers

Vogelsang accounts for outliers by adding dummy variables to the ADF regression. Outliers are detected using an iterative method described in Vogelsang (op. cit., pp. 240–2).

Results of the outlier-robust unit root tests are reported in table 7.5. Typically, most tests for nonstationarity in a time series assume the presence of at most one unit root.

---

74 Additive outliers have an immediate and temporary effect on a time series. The graph of $w_h$ lends support to the view that the outlier, if in fact one exists, is of the additive type as hog prices rebounded rather quickly from their low point.

75 Note that the test reduces to the standard ADF test if no outliers are detected.
Consequently, testing starts with the level of the series and tests up. If the null hypothesis is not rejected, i.e., a unit root is detected, one proceeds by testing the first difference of the series. Since most economic time series have been found to be $I(1)$, testing usually stops at this point. However, Dickey and Pantula (1987) showed that this testing sequence leads to incorrect inferences about the number of unit roots when a series contains more than one unit root. We noted in chapter 5 that most economic time series have at most two unit roots. Thus, according to Dickey and Pantula, a statistically valid testing sequence begins by testing the second difference of the series for a unit root, which is the strategy we have employed. The columns labeled $I(2)$, $I(1)$, and $I(0)$ in table 7.5 represent tests for 2, 1, and 0 unit roots respectively.\footnote{Because $\Delta^4 = (1 - L)(1 - L)(1 + L + L^2 + L^3) = (1 - L)^2(1 + L + L^2 + L^3)$, the testing procedure employed in testing for seasonal unit roots embodies the Dickey and Pantula (1987) strategy.}

The results are mixed, though they do indicate the value of accounting for outliers in the data as several were detected. The tests conclude that $q_b$ and $q_p$ are $I(2)$ (since we are unable to reject the null that each series has a unit root in its first difference), $q$, $y$, $w$, and $q^*$ are $I(1)$, and $w_h$ is stationary. The results for $q_b$ and $q_p$ contrast with those of the HEGY test, which indicate that both series are $I(1)$. Patterson (2000, p. 270) notes that $I(2)$ series are “smoother and more slowly changing than an $I(1)$ series.” However, figure 6.1 shows that neither $q_b$ nor $q_p$ are smooth. In light of this fact and the results of the HEGY tests, we conclude that $q_b$ and $q_p$ are $I(1)$.

The situation with $w_h$ is different, as the results in table 7.5 are consistent with those of the HEGY test. Figure 7.2 on the following page graphs the autocorrelation (ACF) and partial autocorrelation (PACF) functions and 95% confidence bands of $w_h$, $\Delta w_h$, and $\Delta^2 w_h$. The figure indicates that $w_h$ is a stationary AR(1) process. However, the ACF of $\Delta w_h$ gives no evidence that it is overdifferenced, whereas the statistically significant and
negative first-order autocorrelation coefficient of $\Delta^2 w_h$ does suggest overdifferencing (see Patterson 2000, p. 297).

In practice, it is unlikely that many economic time series have one or more roots in their autoregressive polynomials that are precisely equal to one. A better characterization of the property that shocks have a persistent but finite-lived effect on the evolution of a time series lay in the notion of long-memory or fractional integration (Hamilton 1994, p. 448–9). A series is fractionally integrated of order $d$, or $I(d)$, if $0 < d < 1$. The series is stationary if $0 < d \leq 0.5$, and possesses long-memory if $0.5 < d \leq 1$. A somewhat dated review of formal tests of fractional integration is provided in Baillie (1996). This literature is very complex, and we do not endeavor to undertake an analysis here. Nevertheless, preliminary testing for fractional integration provides some support for the notion that $w_h$ possesses long-memory. Furthermore, Patterson (2000, p. 304) argues that for the sake of robust
inference it may be better to treat a stationary, but persistent, series as if it were $I(1)$. That is the approach we take here with respect to $w_h$.

### 7.2.2 Cointegration Tests

Having argued that the variables in the demand relation exhibit (approximately) $I(1)$ behavior, we move on to test whether a linear combination of said variables is cointegrated, in which case a long-run equilibrium relationship exists and the variables have an error correction representation. The two most prevalent methods for testing whether a linear combination of $I(1)$ variables is cointegrated are the single equation method of Engle and Granger (1987) and the vector autoregressive (VAR) systems-based approach of Johansen (1988, 1991).

In the Engle-Granger method, a cointegrating regression is estimated of the form

$$y_t = \alpha_0 + \alpha_1 x_{1,t} + \alpha_2 x_{2,t} + \cdots + \alpha_k x_{k,t} + \epsilon_t,$$  \hspace{1cm} (7.6)

where all variables are assumed to be $I(1)$, and $\epsilon \sim iid(0, \sigma^2_\epsilon)$. If there is a cointegrating relationship between the variables in (7.6), then the linear combination of the variables and the error term are stationary. Thus, a test of cointegration can be conducted by testing the residuals from (7.6) for a unit root using a Dickey-Fuller test. Under the null hypothesis of a unit root, the variables are not cointegrated. It should be noted that because the residuals themselves are estimated, standard Dickey-Fuller critical values are not valid when testing for cointegration. However, MacKinnon (1996) has written a program to calculate response surface critical values for the Dickey-Fuller cointegration test. A drawback of the Engle and Granger approach is that the results are not invariant to choice of normalization, i.e., the regressand. Furthermore, the cointegration test, being essentially a Dickey-Fuller test...
for a unit root, has the same poor power properties, making it not unlikely that the test will fail to detect a cointegrating relationship when in fact one exists.

The method proposed by Johansen (1988, 1991) tests for cointegration within a VAR and is a multivariate generalization of tests for unit roots in a univariate time series. Unlike the single equation approach of Engle and Granger (1987), all variables are assumed to be endogenous in the Johansen framework, and, hence, are treated symmetrically. Consider the general \( p \)th-order VAR\((k) \) given by

\[
Y_t = \mu + \Phi_1 Y_{t-1} + \cdots + \Phi_k Y_{t-k} + \varepsilon_t, \tag{7.7}
\]

where \( Y \) is a \( p \times 1 \) vector of I(1) variables, \( \mu \) is a \( p \times 1 \) vector of constants, \( \Phi_i, i = 1 \ldots k \) is a \( p \times p \) matrix of parameters, and \( \varepsilon \sim iid(0, \Sigma) \) is a \( p \)-dimensional vector of error terms with mean vector \( \theta \) and variance-covariance matrix \( \Sigma \). With a little algebra, we can rewrite (7.7) as

\[
\Delta Y_t = \mu + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_p \Delta Y_{t-p+1} + \Pi Y_{t-1} + \varepsilon_t, \tag{7.8}
\]

where \( \Gamma_i = -(\Phi_{i+1} + \cdots + \Phi_p) \), and \( \Pi = (\Phi_1 + \cdots + \Phi_p - I_p) \) embodies the long-run properties of the system. Clearly, \( \Delta Y_t \) and \( \varepsilon_t \) are stationary, thus attention centers on the term \( \Pi Y_{t-1} \). There are three possibilities. First, if there are no cointegrating relationships in \( Y_t \), then it must be true that \( \Pi = 0 \), in which case (7.8) is a stationary VAR in \( \Delta Y_t \). Second, if \( \Pi \) is of full rank, i.e., \( \rho(\Pi) = p \), then \( Y_t \) must be I(0). To see that this statement is true, assume that \( Y_t \) is I(1) and \( \rho(\Pi) = p \). If \( \Pi \) is a matrix of cointegrating vectors, then it must be true that \( \Pi Y_t = \zeta \) is I(0). Since \( \Pi \) is of full rank, it has a well-defined inverse. It follows that \( Y_t = \Pi^{-1} \zeta \) is I(0). But this statement contradicts the original assumption that \( Y_t \) is I(1), and we are done. Third, if \( \rho(\Pi) = r < p \), then there are \( r \leq p - 1 \) linear combinations of \( Y_t \) that are stationary, i.e., there are \( r \) cointegrating relationships. Any
reduced-rank matrix $\Pi$ can be written as $\Pi = \alpha \beta'$, where $\Pi$ is a $p \times p$ matrix and $\alpha$ and $\beta$ are $p \times r$ matrices.\textsuperscript{77} Substituting this relationship into (7.8) yields

$$
\Delta Y_t = \mu + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + \alpha \beta' Y_{t-1} + \epsilon_t.
$$

Equation (7.9) is known as the vector error correction model (VECM). The cointegrating vectors are contained in the columns of $\beta$, whereas $\alpha$ is the matrix of adjustment parameters.\textsuperscript{78}

Johansen estimates $\Pi$ using maximum likelihood. The estimated $\beta$ consists of the eigenvectors associated with the $r$ largest eigenvalues of $\Pi$. Let $\psi_i$, $i = 1 \ldots p$ denote the eigenvalues of $\Pi$ ordered such that $\psi_1 \geq \cdots \geq \psi_r \geq \psi_{r+1} \geq \cdots \geq \psi_p$. Johansen argues that if there are $r$ cointegrating relationships in the system, then $\log(1 - \hat{\psi}_i) = 0$ for the $p - r$ smallest eigenvalues, i.e., $\psi_{r+1} \ldots \psi_p$. Thus, the estimated eigenvalues can be used to test hypotheses about the number of cointegrating vectors. Johansen develops two statistics to test the cointegrating rank. The first test is based on the trace statistic given by

$$
-T \sum_{i=r_0+1}^{p} \ln(1 - \hat{\psi}_i)
$$

where $r_0$ is the number of cointegrating vectors, and $\hat{\psi}_i$ is the $i$th estimated eigenvalue. The statistic tests the null hypothesis $H_0: r \leq r_0$ against the alternative $H_1: r \geq r_0 + 1$. The second test is based on the maximum eigenvalue statistic, which is given by

$$
-T \ln(1 - \hat{\psi}_i), \quad i = r_0 + 1.
$$

In this case the statistic tests $H_0: r \leq r_0$ against $H_1: r = r_0 + 1$. The test based on the maximum eigenvalue statistic is deemed to be more powerful owing to its more restrictive

\textsuperscript{77}See proposition 3 in Lancaster and Tismenetsky (1985, p. 97).

\textsuperscript{78}The cointegrating vectors are not unique as any linear transformation of $\beta$ will also contain $r$ cointegrating vectors.
alternative hypothesis. Critical values for these statistics can be found in Osterwald-Lenum (1992) and MacKinnon et al. (1999) inter alia.

Our original intent was to use the Johansen framework to test for one or more cointegrating vectors in the demand relation. However, preliminary estimation of the unrestricted VAR(4)—given in general form by (7.7)—indicated the presence of residual autocorrelation in several of the estimated equations. Owing to the limited number of observations in our dataset ($T = 52$) as well as the relatively large dimension of our model ($p = 7$), we were unable to increase the lag length. The presence of autocorrelation is problematic for the Johansen cointegration tests as they are sensitive to the assumptions of the model, particularly the requirement that the errors be independent. Indeed, Huang and Yang (1996) present Monte Carlo evidence showing that the Johansen tests are biased toward finding cointegration when no cointegrating relationships exist. In view of this fact, we test for cointegration using the Engle-Granger two-step method.

The cointegrating regression was estimated by two-stage least squares using supply variables as instruments to control for shifts in the hog supply curve. The instruments chosen were the logarithms of barrow and gilt slaughter and the second lag of the pig crop. The estimated equation is given by

$$w_{h,t} = \alpha_0 + \lambda q_t^* + \alpha_1 q_t + \alpha_2 q_{b,t} + \alpha_3 q_{p,t} + \alpha_4 y_t + \alpha_5 w_t + \pi_1 S_{1,t} + \pi_2 S_{2,t} + \pi_3 S_{3,t} + \delta t + \delta D_{98,t} + \epsilon_t, \quad (7.10)$$

where the variables are defined in chapter 6, the $S_i$ are seasonal dummies, $t$ is a linear trend, $D_{98}$ is a dummy variable accounting for the outlier in hog prices that occurred in the fourth quarter of 1998, and $\epsilon \sim iid(0, \sigma^2)$. Results are reported in table 7.6 on the next page. The $t$-statistics are shown even though it is likely that they are not valid for
Table 7.6–Cointegrating regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Estimate</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_t^*$</td>
<td>$\alpha_2$</td>
<td>0.001</td>
<td>0.792</td>
</tr>
<tr>
<td>$q_t$</td>
<td>$\alpha_3$</td>
<td>-3.719</td>
<td>-7.331</td>
</tr>
<tr>
<td>$q_{b,t}$</td>
<td>$\alpha_4$</td>
<td>-0.323</td>
<td>-0.475</td>
</tr>
<tr>
<td>$q_{p,t}$</td>
<td>$\alpha_5$</td>
<td>-0.266</td>
<td>-0.289</td>
</tr>
<tr>
<td>$y_t$</td>
<td>$\alpha_6$</td>
<td>0.380</td>
<td>0.135</td>
</tr>
<tr>
<td>$w_t$</td>
<td>$\alpha_7$</td>
<td>1.990</td>
<td>1.104</td>
</tr>
<tr>
<td>$S1$</td>
<td>$\pi_1$</td>
<td>-0.219</td>
<td>-3.308</td>
</tr>
<tr>
<td>$S2$</td>
<td>$\pi_2$</td>
<td>-0.132</td>
<td>-2.317</td>
</tr>
<tr>
<td>$S3$</td>
<td>$\pi_3$</td>
<td>-0.322</td>
<td>-4.096</td>
</tr>
<tr>
<td>$D_{98}$</td>
<td>$\delta$</td>
<td>-0.562</td>
<td>-4.664</td>
</tr>
<tr>
<td>$t$</td>
<td>$\delta$</td>
<td>0.027</td>
<td>1.485</td>
</tr>
<tr>
<td>Constant</td>
<td>$\alpha_0$</td>
<td>31.862</td>
<td>1.158</td>
</tr>
</tbody>
</table>

1, 5, and 10% sig. levels denoted by ***, **, and *;
$T = 50$; $R^2 = 0.808$; $F_{11,38} = 14.87^{***}$

inference. A Sargan (1958) test of overidentifying restrictions was used to check the validity of the instruments. The test statistic has a $\chi^2$ distribution where $m$ equals the number of overidentifying restrictions. We calculated a test statistic of 1.660 with a $p$-value of 0.198. Thus, the choice of instruments is valid. Of particular interest is the fact that the coefficient of $q^*$, the long-run estimate of oligopsony power, equals zero. Thus, to the extent that these results are not spurious, there is no evidence of oligopsony power in the long-run.

To determine whether the variables in table 7.6 (exclusive of the deterministic regressors) are cointegrated, a Dickey-Fuller test for a unit root was conducted using the residuals from equation (7.10). The results of the Dickey-Fuller regression are reported in table 7.7.

---

79Patterson (2000, p. 337) writes that “a complete empirical model . . . may involve lags of [the explanatory] variables; . . . to be validly excluded from a cointegrating regression they must be stationary.” If this is not true, then residuals are likely to be autocorrelated and heteroskedastic, in which case the standard errors are incorrect.
\[
\Delta \hat{\epsilon}_t = -0.605 \hat{\epsilon}_{t-1} + \hat{u}_t
\]

Sample Period: 1988.II to 2000.IV 
\((T = 51)\)

Table 7.7–Dickey-Fuller test for cointegration

No augmentation was necessary to obtain i.i.d. residuals. The test statistic equals -4.645, which is highly significant using regular Dickey-Fuller critical values. However, as mentioned in the previous section, these critical values are not appropriate when testing for cointegration. Correct critical values are obtained from MacKinnon’s (1996) urcdist program. Using this program we calculated a \(p\)-value of 0.106. Thus, our results are on the cusp of the critical region for a 10% significance level. In view of the unknown bias that pretests for unit roots impart to cointegration tests (see Maddala and Kim 1998), and our \textit{a priori} belief that a long-run relationship does exist among variables in the demand relation, we believe sufficient evidence exists to conclude that these variables are indeed cointegrated.

### 7.2.3 Estimation Results

In this section we present the estimation results for the demand relation, the final specification of which is given by

\[
\Delta w_{h,t} = \delta_0 + \sum_{j=0}^{k-1} \delta_j^x \Delta q_{t-j}^x + \sum_{j=1}^{k-1} \delta_j^s \Delta w_{h,t-j} + \sum_{j=0}^{k-1} \delta_j^\epsilon \Delta q_{t-j} + \sum_{j=0}^{k-1} \delta_j^\eta \Delta q_{t,j} + \sum_{j=1}^{k-1} \delta_j^\lambda \Delta q_{t-j} + \sum_{j=0}^{k-1} \delta_j^\pi \Delta q_{t-j} + \sum_{i=1}^{3} \pi_i S_{i,t} + \alpha \left[ w_{h,t-k} - \Lambda q_{t-k}^x - \xi_1 q_{t-k} - \xi_2 q_{b,t-k} - \xi_3 q_{p,t-k} - \xi_4 y_{t-k} - \xi_5 w_{t-k} \right] + \xi_t, \tag{7.11}
\]
where, with the exception of the three seasonal dummy variables \( (S_i) \), equation (7.11) is identical to (4.28). Before discussing the results, note that the long-run coefficients \( \xi_i, \ i = 1 \ldots 5 \), and \( \Lambda \), are not estimated directly. Let the true values of the coefficients that are estimated be given by \( \xi^*_i, \ i = 1 \ldots 5 \), and \( \Lambda^* \), where

\[
\xi_i = a \xi_i^* \\
\Lambda = \alpha \Lambda^*.
\]

Solving these equations for the long-run coefficients yields

\[
\begin{align*}
\xi_i &= \frac{\xi^*_i}{a} \quad (7.12a) \\
\Lambda &= \frac{\Lambda^*}{\alpha}. \quad (7.12b)
\end{align*}
\]

Thus, the long-run coefficients are nonlinear functions of the adjustment parameter, \( a \).

Equations (7.12a) and (7.12b) call for a nonlinear estimator. However, Bårdsen (1989) has shown that the error correction term can be factored such that equation (7.11) can be estimated using OLS. This factorization, known as the Bårdsen transformation, allows us to obtain an OLS estimate of the adjustment parameter, \( \hat{a} \), which is the coefficient of \( w_{h,i-k} \).

Substituting \( \hat{a}, \xi^*_i, \) and \( \hat{\Lambda}^* \) into equations (7.12a) and (7.12b) yield estimates of the long-run parameters. Bårdsen also provides a formula for calculating the standard errors of the long-run coefficients.

Equation (7.11) was estimated by two-stage least squares using supply variables as instruments to control for shifts in the supply curve. The instruments used included a composite feed price and a time trend. The Sargan test for the validity of the instruments

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\(^{80}\) The 1998 outlier dummy and its lagged differences were neither individually nor jointly significant and so were excluded from the final model.

\(^{81}\) The instruments used in estimating the cointegrating regression, (equation (7.10)), were rejected using the Sargan test for the validity of instruments.
Table 7.8–Misspecification tests

<table>
<thead>
<tr>
<th>Test</th>
<th>Order ($p$) 1</th>
<th>Order ($p$) 2</th>
<th>Order ($p$) 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM($p$)</td>
<td>0.041 (0.842)</td>
<td>0.056 (0.946)</td>
<td>0.151 (0.960)</td>
</tr>
<tr>
<td>ARCH($p$)</td>
<td>0.112 (0.743)</td>
<td>0.142 (0.889)</td>
<td>0.081 (0.987)</td>
</tr>
</tbody>
</table>

$p$-values in parentheses
See Hendry and Doornik (2001)

yielded a test statistic of 1.848 with a $p$-value of 0.174. Thus, we are unable to reject the null hypothesis that the instruments are independent of the regression residuals. Table 7.8 reports the $F$-statistic variants of tests for residual autocorrelation and autoregressive conditional heteroskedasticity. The tests give no indication of misspecification.

Estimation results are reported in table 7.9 on page 79. We found $k = 3$ lags was sufficient to account for residual autocorrelation. The overall fit of the estimated equation is quite good with an $R^2 = 0.85$. Somewhat surprisingly, almost two-thirds of the coefficients are statistically significant.

Of particular interest, however, are the short- and long-run estimates of oligopsony power, $\lambda_0^*$ and $\Lambda$. Like the index of oligopoly power (see the discussion following equation 3.5 on page 18), the estimate of oligopsony power should lie in the range between 0 and 1 inclusive. A value of 0 corresponds to perfect competition, a value of 1 to pure monopsony, and intermediate values correspond to various oligopsony regimes. In this regard, the estimates of $\lambda_0^*$ and $\Lambda$ in table 7.9 prove somewhat problematic. Both coeffi-

---

82 There were not enough observations to conduct either the Breusch-Pagan or White heteroskedasticity tests.

83 Results reported by Steen and Salvanes (1999) attributed a lack of statistically significant coefficient estimates to problems of multicollinearity.
cient estimates are negative implying an oligopsony markup, i.e., producers are better off under monopsony, rather than a markdown. The estimate of $\lambda^*_0$, moreover, is statistically significant. These facts notwithstanding, one should make a distinction between statistical and economic significance. The 95 percent confidence intervals for both $\lambda^*_0$ and $\Lambda$ contain zero and the magnitudes of the estimates are very small. It seems likely that the negative signs on the coefficient estimates reflect the highly aggregative nature of the data as well as possible specification errors in either one or both of the supply and demand equations.

In any event, the small magnitudes of $\lambda^*_0$ and $\Lambda$ seem to point to the non-existence of oligopsony power in the slaughter hog market. A possible explanation for this finding is that packers as a whole behaved competitively during much or all of the period covered by this study. This possibility seems likely, especially when one considers that oligopsony power has been found to be very small—when detected at all—in several studies of the more highly concentrated beef packing sector. In this regard, our results are largely in agreement with those of other studies that have analyzed the competitiveness of livestock markets (see Azzam and Anderson 1996; Azzam 1998a). It should be noted, however, that our result cannot nor should not be taken as evidence that the U.S. spot market for slaughter hogs is competitive. It could be the case, for instance, that pork packing firms did engage in anticompetitive conduct as industry concentration increased, but that the information contained in the data is not sufficiently strong to detect such conduct using the empirical methods employed in this paper.

With the exception of the estimate of oligopsony power, all other long-run parameters are statistically significant. The estimated demand relation is downward sloping as ex-

---

84 See Azzam and Anderson (1996); Azzam (1998a). In 1999, the top four beef packers accounted for 70.4% of cattle slaughter; the corresponding figure in pork packing was 56.2% (USDA-GIPSA 2000).

85 We would like to thank to Dr. James MacDonald of USDA-ERS for bringing this point to our attention.
pected and own-price elastic. However, some of the results run counter to expectations. For example, the estimated coefficient of the quantity of beef, $\xi_2$, shows beef and pork to be complementary products. More problematic are the estimated coefficients of the income and packing plant wage variables. The estimated income coefficient, $\xi_4$ indicates that pork is an inferior good, whereas the estimated wage coefficient, $\xi_5$ implies that increases in the packing plant wage shift residual pork demand to the right. This latter result was also obtained by Azzam and Park (1993). They argue that this finding may reflect the fact that the aggregate packing plant wage may be a poor proxy for the industry-specific wage, in this case the wage paid in pork packing plants.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Estimate</th>
<th>$t$-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$\delta_0$</td>
<td>56.717</td>
<td>1.837*</td>
</tr>
<tr>
<td>$S1$</td>
<td>$\pi_1$</td>
<td>-0.077</td>
<td>-0.351</td>
</tr>
<tr>
<td>$S2$</td>
<td>$\pi_2$</td>
<td>-0.646</td>
<td>-2.251**</td>
</tr>
<tr>
<td>$S3$</td>
<td>$\pi_3$</td>
<td>-0.603</td>
<td>-2.442**</td>
</tr>
<tr>
<td>$\Delta w_{h,t-1}$</td>
<td>$\delta_{01}$</td>
<td>-1.059</td>
<td>-3.468***</td>
</tr>
<tr>
<td>$\Delta w_{h,t-2}$</td>
<td>$\delta_{02}$</td>
<td>-0.741</td>
<td>-2.339***</td>
</tr>
<tr>
<td>$\Delta q_t$</td>
<td>$\delta_{10}$</td>
<td>-4.542</td>
<td>-3.786***</td>
</tr>
<tr>
<td>$\Delta q_{t-1}$</td>
<td>$\delta_{11}$</td>
<td>-3.624</td>
<td>-2.611**</td>
</tr>
<tr>
<td>$\Delta q_{t-2}$</td>
<td>$\delta_{12}$</td>
<td>-0.696</td>
<td>-0.615</td>
</tr>
<tr>
<td>$\Delta q_{b,t}$</td>
<td>$\delta_{20}$</td>
<td>-0.205</td>
<td>-0.198</td>
</tr>
<tr>
<td>$\Delta q_{b,t-1}$</td>
<td>$\delta_{21}$</td>
<td>-1.585</td>
<td>-1.443</td>
</tr>
<tr>
<td>$\Delta q_{b,t-2}$</td>
<td>$\delta_{22}$</td>
<td>-2.071</td>
<td>-1.583</td>
</tr>
<tr>
<td>$\Delta q_{p,t}$</td>
<td>$\delta_{30}$</td>
<td>2.395</td>
<td>1.946*</td>
</tr>
<tr>
<td>$\Delta q_{p,t-1}$</td>
<td>$\delta_{31}$</td>
<td>2.831</td>
<td>2.446**</td>
</tr>
<tr>
<td>$\Delta q_{p,t-2}$</td>
<td>$\delta_{32}$</td>
<td>4.551</td>
<td>2.465**</td>
</tr>
<tr>
<td>$\Delta y_t$</td>
<td>$\delta_{40}$</td>
<td>-6.614</td>
<td>-1.101</td>
</tr>
<tr>
<td>$\Delta y_{t-1}$</td>
<td>$\delta_{41}$</td>
<td>-14.233</td>
<td>-2.203**</td>
</tr>
<tr>
<td>$\Delta y_{t-2}$</td>
<td>$\delta_{42}$</td>
<td>-9.114</td>
<td>-1.643</td>
</tr>
<tr>
<td>$\Delta w_t$</td>
<td>$\delta_{50}$</td>
<td>4.400</td>
<td>1.093</td>
</tr>
<tr>
<td>$\Delta w_{t-1}$</td>
<td>$\delta_{51}$</td>
<td>0.542</td>
<td>0.172</td>
</tr>
<tr>
<td>$\Delta w_{t-2}$</td>
<td>$\delta_{52}$</td>
<td>5.161</td>
<td>1.488</td>
</tr>
<tr>
<td>$\Delta q_t^*$</td>
<td>$\lambda_{0}^*$</td>
<td>-0.003</td>
<td>-2.044*</td>
</tr>
<tr>
<td>$\Delta q_{t-1}^*$</td>
<td>$\lambda_{1}^*$</td>
<td>-0.004</td>
<td>-1.990*</td>
</tr>
<tr>
<td>$\Delta q_{t-2}^*$</td>
<td>$\lambda_{2}^*$</td>
<td>0.000</td>
<td>0.252</td>
</tr>
<tr>
<td>$w_{h,t-3}$</td>
<td>$\alpha$</td>
<td>-0.532</td>
<td>-2.540**</td>
</tr>
<tr>
<td>$q_{t-3}$</td>
<td>$\xi_1$</td>
<td>-2.952</td>
<td>-1.998**</td>
</tr>
<tr>
<td>$q_{b,t-3}$</td>
<td>$\xi_2$</td>
<td>-4.411</td>
<td>-1.895**</td>
</tr>
<tr>
<td>$q_{p,t-3}$</td>
<td>$\xi_3$</td>
<td>8.568</td>
<td>2.284**</td>
</tr>
<tr>
<td>$y_{t-3}$</td>
<td>$\xi_4$</td>
<td>-16.421</td>
<td>-1.763**</td>
</tr>
<tr>
<td>$w_{t-3}$</td>
<td>$\xi_5$</td>
<td>20.952</td>
<td>2.270**</td>
</tr>
<tr>
<td>$q_{t-3}^*$</td>
<td>$\Lambda$</td>
<td>-0.002</td>
<td>-0.963*</td>
</tr>
</tbody>
</table>

1, 5, and 10% sig. levels denoted by ****, ***, and *;
$T = 49$; $R^2 = 0.849$; $F_{30,18} = 3.669^{***}$

* Calculated using Børden approximation

Table 7.9–Estimation results for (7.11)
CHAPTER 8

CONCLUSION

The purpose of this study has been to estimate oligopsony power of pork packing firms in the U.S. spot market for slaughter hogs using a structural econometric model. In recent years the U.S. pork industry has undergone significant structural change as a result of a process termed agricultural industrialization. Certain of these changes, such as a more concentrated packing sector and greater use of captive supplies, prompted concerns by market participants and legislators about the competitiveness of spot hog markets. To date, most studies of market power in the livestock industry have focused on beef packing, even though the beef and pork industries share similar structures. This state of affairs is likely due to the fact that the level of concentration is significantly higher in beef packing than in pork packing. Nevertheless, given public policy concern over changes in the pork industry (U.S. Congress 1999, 2000), this study fills a clear need.

We estimated oligopsony power of pork packing firms using an NEIO model developed by Steen and Salvanes (1999). This method reformulates within an error correction framework the model developed by Just and Chern (1980), Bresnahan (1982), and Lau (1982). The advantage of this approach is that by accounting for short-run deviations from long-run equilibrium, more complete use is made of the information in the data to yield short- and
long-run estimates of market power. Relative to other NEIO approaches, the Steen and Salvanes model also has modest data requirements and uses relatively simple functional forms for supply and demand. The results of our model yield no evidence that pork packing firms were able to exert oligopsony power in spot markets in either the short- or long-run during the 1988-2000 period.

At this point it is useful to step back and reflect briefly on the Steen and Salvanes method. Although it yields short- and long-run average estimates of market power, the validity of the approach hinges on the time series properties of the data. As such, it is relatively easy to lose sight of the economic forest for the time series trees. More specifically, the error correction model is valid only if all variables are integrated of the same order—usually \( I(1) \)—and are cointegrated. The requirement that all variables have a unit root can be especially problematic in that statistical tests of the unit root null are notorious for their low power. Indeed, Christiano and Eichenbaum (1990) argue that it is virtually impossible to distinguish between stationary and nonstationary variables with sample sizes typically used in empirical analyses. This criticism is relevant to this study, which only had 52 observations available for estimation. Furthermore, cointegration tests, particularly those that rely on the Johansen (1988, 1991) approach, are sensitive to the underlying assumptions of the model.

In light of these criticisms, it is natural to ask what could be done to improve upon the analysis. We have several recommendations. First, the stationary/unit root dichotomy is probably too rigid. In other words, it is highly unlikely that any variable has one or more roots that are exactly equal to one. A more fruitful approach would allow for variables that are fractionally integrated, i.e., mean reverting, but not covariance stationary. Second, the supply slope parameters in our model were obtained indirectly. It might be useful to
develop a more complete model of hog supply that incorporates the breeding herd as a capital asset. Third, in view of the finding of Hyde and Perloff (1995) that estimates of market power are sensitive to functional form, it would be useful to assess the robustness of the results reported in this study by undertaking a sensitivity analysis. Fourth, Sexton (2000) has pointed out that a failure to find empirical evidence of market power may be a consequence of assuming one side of the market to be competitive. Thus, it might be helpful to re-estimate the model allowing packers to have both oligopsony and oligopoly power.

These suggestions notwithstanding, we believe that our results do in fact accurately reflect the nature of competition in spot hog markets during the 1988-2000 period. For one thing, the dramatic rise in industry consolidation and growth in captive supplies accelerated in the second half of the 1990s. Furthermore, Morrison Paul (2001) argues that findings of market power in the livestock industry may be due instead to technologically driven economies of scale. But given that (i) captive supplies do have a strategic rationale (Sexton and Zhang 2001), (ii) the pork industry continues to become more concentrated, and (iii) contract prices are tied to spot markets, it is important that policymakers remain vigilant in monitoring the extent of competition in slaughter hog markets. In this regard, it would probably be useful to re-estimate the model used in this study once additional data becomes available, with proper allowance for structural change.
BIBLIOGRAPHY


