Competition in Fresh Produce Markets

An Empirical Analysis of Marketing Channel Performance

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Abstract

Fresh produce growers/shippers believe that consolidations in grocery retailing may empower retailers to act less competitively. This study evaluates the extent to which retailers exercise market power in buying from growers and selling to consumers. Sales data for retail chains in six U.S. metropolitan markets are used along with data on grower prices for an analysis on apples, grapes, oranges, and grapefruit. The evidence varies by commodity, but does consistently point to the exercise of market power by retailers in consumer sales; less support is found on buying market power. Market power varies over time and with produce volume.

Keywords: Fresh fruits and vegetables, fresh produce, fresh produce marketing channels, supermarket, market power, competition, trading practices.

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Executive Summary

- Fresh produce growers, shippers, and their trade organizations are concerned that the wave of mergers among grocery retailers may reduce the competitiveness of the retail grocery industry - both on the buying and selling sides.
- This study represents a comprehensive analysis of retailers' ability to set noncompetitive prices in the fresh apple, table grape, fresh California orange, and Florida grapefruit markets in both their commodity purchases and retail sales. In addition to evaluating retailers' price setting ability, we also evaluate other dimensions of price performance, including where in the marketing channel the price is set, the extent to which changes in price are transmitted through the channel, and the extent to which retailers hold retail prices fixed.
- The data used in this analysis consist of two years (1998 and 1999) of weekly retail-scanner price and sales data from six major geographically dispersed metropolitan markets-Albany, Atlanta, Chicago, Dallas, Los Angeles, and Miami. Within each market, most major retail chains are represented in the data. At the shipper level, our data consist of shipping-point prices and volumes obtained from either the USDA or individual commodity commissions. These data are supplemented with data from a variety of other sources to account for transportation costs, marketing costs, and variations in factors that are critical to the demand or supply of each commodity.
- Preliminary analyses of the retail and shipping-point price data find that: (1) prices for semi-perishable fruits are formed at the shipping point; (2) retail prices respond more rapidly to shipping-point price increases than to declines, although this result was less significant for apples than for the other commodities; (3) retail prices are fixed relative to the variation that occurs at the shipper level. These latter two results are consistent with retailers' possessing some control over prices in both the commodity and retail markets, while the first suggests that retailers determine the price they pay for fruit before they set the price they charge to consumers.
- If retailers are able to charge noncompetitive prices to consumers, or pay noncompetitive prices to growers, then there must be some way that they agree among themselves, albeit tacitly, to not undercut each other in consumer markets nor outbid each other in product markets. We test for such agreements using a statistical model of fresh fruit pricing based on the reasoning that rival retailers use price thresholds (trigger prices) to instigate punishments for those who cheat on price maintenance agreements. We estimate this model by using an approach that allows for the possibility that prices do indeed follow a "step-like" path over time, where retail prices (shipper-level prices) fall (rise) during periods of punishment and then return to the collusive path once order is restored.
- The results vary by commodity. For apples, we find evidence of both buyer and seller power that is both statistically and economically significant in virtually all market / chain pairs. For fresh grapes, we find strong evidence of retailers' ability to set price in consumer markets, but little support of this same power in input markets. Retailers also appear to possess a considerable degree of control over the prices consumers pay for oranges, but little control over grower prices. Grapefruit buyers exercise a significant degree of buying power in roughly 60 percent of the sample cases, but consistently set imperfectly competitive prices in the output market.
- Retailer power to set prices in both input and output markets tends to fall with the amount of commodity sold. We interpret this as evidence that periodic promotions serve as facilitating mechanisms for the tacitly cooperative agreement followed by rival retailers. This conclusion is supported by the fact that the frequency of punishments is similar to the frequency of these promotional periods and by our observation that some chains exhibit imperfectly competitive behavior, while others do not.
- Future research in this area should focus on areas of specific and emerging concern among government antitrust officials, consumer groups, and grower associations. Specifically, data on off-invoice fees should be gathered by appropriate government oversight agencies.

Introduction

Benefits of Retail Consolidation

In 50 years, the prolonged stock market boom of the 1990s will be remembered for many things, not least of which is the crest of the largest wave of merger and acquisition activity in history. Virtually every sector of the economy experienced massive consolidation as companies used inflated share values as currency in buyout after buyout. The retail grocery industry was no exception. Between 1996 and 1999, there were 385 mergers in the grocery industry and the acquired firms in these transactions had over $67 billion in annual sales. Whereas the top eight grocery firms had a national market share of 26 percent in 1987, their proportion of total grocery sales rose to 37 percent by 2000. In general, shareholders applauded each transaction and awarded consolidation with higher and higher valuations, firmly believing management's claims of unlocking greater efficiencies in purchasing and a larger presence in retail markets. However, few consider exactly what these "efficiencies" mean for suppliers upstream and consumers downstream from the merged retailers. If produce retailers truly are reaping efficiencies as a result of these mergers, then society as a whole is better off as produce will sell for less and stores will find that they must keep a stock of the best-quality produce or risk losing customers. However, if consolidation facilitates imperfectly competitive behavior, then the economic performance of the fresh produce marketing channel may indeed be impaired.

Evidence of Imperfect Competition

Evidence of such poor performance is, however, difficult to come by. It is now commonly recognized among economists that a certain industry structure does not necessarily imply a particular mode of conduct, nor a given level of performance when benchmarked against the competitive ideal (Geroski). However, because structure is more readily observable than either conduct or performance, it is necessary to have methods of obtaining evidence from available data that are widely accepted, rigorous, and consistent with the way in which prices and other decision variables are generated in the real world. Although anecdotal evidence of unfairness nearly always arises when an outcome is subject to negotiation and relative bargaining strength, such evidence hardly provides a sufficient basis upon which to justify intervening in an otherwise free marketplace. The weakness of anecdotal evidence is particularly apparent when a bargaining situation does not necessarily result in observable outcomes, such as market prices or shipment-orders, but rather side-payments or incentives that are maintained as proprietary corporate information. Consequently, it is necessary to apply statistical methods of acquiring evidence from data that are readily observable in order to assess the competitiveness of a given industry.

Buying and Selling Market Power

Unlike traditional agricultural commodities such as grain, cotton, or cattle, fresh fruits and vegetables are generally not used as inputs to further processing by their buyer. Rather, because the channel is commonly more direct between the grower-shipper and the ultimate consumer, deviations from perfectly competitive behavior may appear on either (or both) of two levels: on the supplier/buying side or on the output/retail selling side.[2] In either case, market power may be evident in either prices that are higher (lower) to consumers (shippers) than in competition or through some form of a rent extraction mechanism such as side or off-invoice payments. While evidence of the former lies in readily observable market prices, evidence of the latter tends to be of a weaker, anecdotal form. Indeed, one of the most important implications of this work is that if government antitrust agencies are truly concerned with these practices, they need to develop some method of acquiring the appropriate data on their use. With regard to the former question, however, pricing strategies by produce buyers are likely to depend critically upon the nature of the specific commodity in question.

Perishable Versus Semi-Perishable

If retailers with market power can either offer noncompetitive prices or offer competitive prices but with some form of off-invoice payment expected from the grower, then we must examine the motives and posit the likelihood of both strategies if real-world pricing data are to have any resonance. Because a buyer's incentive to pay competitive per-unit prices and levy an off-invoice fee (the latter strategy) rises the more responsive is supply to price changes, we expect to see imperfectly competitive or monopsony pricing the less responsive is industry supply. Clearly, with a relatively

[2] Typically, 43 percent of fresh produce is marketed directly from growers to retailers; larger retailers (those with annual sales greater than $1.5 billion) may obtain 66 percent of their supplies directly from growers.

fixed (inelastic) supply, retailers can reduce the prices they pay by a relatively large amount before suppliers are no longer willing to bring their goods to market. If supply is highly responsive (elastic), on the other hand, then a similar pricing strategy will mean that retailers are left with little to sell to consumers and their total profit falls accordingly.

In fact, the distinction between elastic and inelastically supplied fruits and vegetables underlies the two distinctly different modeling strategies that appear in other studies of imperfect competition in fresh produce markets (see also Sexton, Zhang, and Chalfant). Whereas we are more likely to see evidence of some degree of monopsony pricing among the highly perishable commodities (tomatoes and lettuce, for example), the opposite is true for goods that are semi-storable and, hence, more elastic in supply.[3] Apples, oranges, grapefruit, and table grapes can each, to a differing extent, be kept on hand until prices are more favorable. In this case, buyers may be more likely to offer competitive prices, but then extract producer profits through some form of a fixed fee. From a social perspective, this outcome is more desirable than the first because consumers are not deprived of a commodity that they would have otherwise bought at market prices. Empirical evidence of either competitive or noncompetitive pricing in fresh produce is, however, virtually nonexistent.

Objectives of Study

We hope to determine whether retailers are able to exercise market power in either their produce buying or selling activities. Because produce markets typically differ substantially on the basis of both geography and commodity, our empirical example considers a number of products and retail markets. Namely, we examine the markets for apples, grapes, fresh oranges, and fresh grapefruit in six regionally disparate retail markets - Albany, Atlanta, Chicago, Dallas, Los Angeles, and Miami. Prior to describing the logic underlying the empirical approach we apply, however, the report begins with a consideration of three key issues in any analysis of commodity pricing: (1) the locus of price determination, (2) the symmetry of retail price adjustment to upward and downward farm price movements, and (3) the "fixity" of retail prices. These issues concern exactly who "sets" fruit prices in the U.S. and how responsive they are to changes in underlying forces of supply and demand. This section also describes in some detail the data used in this study, and the possible limitations it presents for the study of market power.

The next section uses the results of this preliminary data analysis to develop an economic model of retail and grower-level fresh fruit pricing that allows for the possibility that retailers exercise market power in both their buying and retail selling activities. By allowing the degree of market power to vary with supply, we test hypotheses regarding the relative importance of scarcity and retailer marketing strategies such as category management and periodic price promotions.

The report concludes by drawing some implications for the conduct of retail buyers and suppliers of fresh fruit. This section also identifies some of the key issues that remain to be resolved in understanding the efficiency with which produce prices are formed and whether or not retail concentration—if it, in fact, contributes to the exercise of market power—is necessarily to be feared on the basis of pricing evidence alone.

[3] As a reviewer notes, the relationship between storability and elasticity is not one-to-one, but it is clear that on a weekly basis suppliers have far more alternatives for their output if it is potentially storable, exportable or otherwise withheld from the market.

Describing Price Formation in Semi-Perishable Produce Markets

Importance of Understanding Price Dynamics

Understanding the way prices are formed in an industry first requires thorough knowledge of both the institutions that surround the price formation process and the price dynamics that arise as a result. With respect to retail produce sales, marketers both at the retail and shipper levels are becoming increasingly sophisticated. As a result, they are relying less and less on open markets and arms-length transactions to buy and sell fruit, and are instead developing institutions that reflect the greater efficiencies and certainty of longer term trading relationships, such as contracts, preferred-supplier agreements, and participation in automatic inventory replenishment systems. In fact, 56 percent of all produce shippers used retail contracts for at least 10 percent of their shipments in 1997 (McLaughlin et al.). Whereas fundamental issues of price determination and causality were once thought to be well understood, they are less clear now with the proliferation of various retail pricing strategies driven by category management, efficient consumer response, periodic promotions, or everyday-low-price policies. Central to the development of any model of retail and supplier price determination, therefore, is an understanding of how pricing strategies influence how, and where, prices are determined.

Three Critical Pricing Issues

There are essentially three issues to be determined: (1) the locus of price determination, (2) the symmetry of price determination from the locus to the market, and (3) the ability or apparent tendency of prices to adjust to fluctuations in supply and demand, or to move toward equilibrium. Empirically, the locus of price determination is found indirectly, by inferring from the co-movement of prices at different levels of the marketing channel the direction of causality. If price is determined at the shipper level, then shipping-point prices cause retail or wholesale prices and vice versa.

Commonly, tests of causality are used for this purpose and, in general, tend to show that prices are formed in the middle market. However, with the declining importance of the traditional middleman and transactions increasingly conducted between buyers for large regional grocery chains and large, vertically integrated grower-packer-shippers, the locus of price discovery is not only uncertain, but is likely to be changing over time. Because this study investigates the performance of the entire marketing channel, the locus of price discovery is of more than notional interest, with implications for the well being of producers and consumers as well.

Existing Studies on Price Formation In Agriculture

Given the current low rate of inflation, growers fear that retailers' inability to pass cost increases onto consumers will mean that shipping-point prices will reflect higher marketing costs by being pushed below competitive levels. This fear depends upon where prices are first formed, or the "locus of price determination." Among empirical studies, this locus of price discovery is not necessarily found to be at the shipper level as is commonly assumed. In fact, Hahn shows that price discovery in beef and pork markets can occur at either wholesale or retail. Similarly, Wohlgenant and Mullen show that retail beef prices do not "cause" or lead to farm prices in a statistical sense, so the retail level cannot be the point of discovery. Ward argues that price discovery occurs at the level that is best able to assimilate information regarding either changes in demand or supply.

Because the wholesale sector tends to have fewer firms than either the farm or retail sectors, the cost of obtaining price information is lower and information moves within firms more readily than between them (Salop and Stiglitz), so price discovery is more likely to occur at wholesale. Ward finds support for this argument using data on farm, wholesale, and retail prices for a group of fresh vegetables. Heien, on the other hand, finds that wholesale and retail prices are independent for apples, tomatoes, and lettuce, but influence each other for canned tomatoes and fresh orange juice. These indeterminate results for fruits and vegetables are supported by Lamm and Westcott, who find shipper and retail produce prices to be independent. However, Bernard and Willett's study of price spreads in the broiler industry provides support both for Ward's theoretical and empirical results. Others, such as Powers, Wohlgenant and Clary, and Pick et al., instead merely assume that farm prices drive retail prices. Pick et al. do not even consider wholesale citrus prices because, as is the case for many fruits, retailers buy directly from shippers and do not use wholesalers. Understanding who is responsible for determining prices is a logical starting point for further investigation into how efficient the price determination process is, and how competitive the result may be.

Symmetry of Price Adjustment

Another indirect indicator of the competitiveness of price adjustment is whether upward and downward price movements at the locus are translated to the other market with equal speed and completeness. The speed with which retail prices adjust to price changes originating at the shipping point is often interpreted as an indicator of either retailers using their control over price to temporarily widen margins, or of the competitiveness of the retail sector. For example, Pick et al. provide evidence of lags of up to 3 weeks for retailers to adjust to farm price changes, while Ward finds no lag in tomato price adjustment. Others find evidence of significant adjustment lags in dairy products (Kinnucan and Forker), lettuce (Powers), groups of food products (Heien), frozen orange juice (Shonkwiler and Taylor), beef products (Wohlgenant; Schroeder and Goodwin; Bailey and Brorsen), broilers (Bernard and Willet), and rice (Brorsen et al.).

If there are indeed significant costs of adjusting retail prices in response to upstream changes in supply or demand, or if prices are inherently uncertain and retailers have irreversible investments in maintaining price points (Dixit and Pindyck), then these lags may be perfectly consistent with a competitive equilibrium. Many, however, interpret such behavior as imperfect competition (Hahn), especially when sluggish adjustment is accompanied by asymmetrical price changes. For this reason, studies that investigate the rate of price adjustment often also consider the symmetry of response of affected prices to changes in causal prices.[4] Defining retail prices as affected and shipping-point or wholesale prices as causal, symmetrical retail price response means that retailers pass prices changes downstream equally irrespective of whether the change is an increase or a decrease.

Asymmetry in price adjustment is often interpreted as poor pricing performance, where retailers are either absorbing price increases to avoid losing market share or failing to expeditiously pass through price reductions in order to temporarily raise their margins. Among studies of produce industries, Powers provides evidence of the former case in fresh lettuce and Ward for various fresh vegetables, while Pick et al. find that citrus retailers are more likely to raise margins in response to shipping-point price changes, although their results vary by both product and market. This issue is also considered at length in other industries by Kinnucan and Forker (dairy products), cattle (Bailey and Brorsen), pork (Boyd and Brorsen), and broilers (Bernard and Willett). Of course, concern over the speed of price transmission is moot if retail prices are found to be essentially fixed and the retail level is the locus of price determination.

Causes of Price Fixity at Retail

Many argue that the ability to set and maintain retail price points amid considerable variation in shipping-point prices is itself evidence of market power. Moreover, our interviews with shippers and brokers suggest that retail price fixity is seen as the most visible and egregious embodiment of market power because fixed price strategies mean that supply and demand cannot function properly to clear the market during times of oversupply. Indeed, there is little argument that retail prices move very little relative to shipping-point prices. Shonkwiler and Taylor show that desired produce prices must change by a significant amount before prices change in actuality. Powers develops a model based on similar logic to show that price-adjustment costs are largely responsible for the apparent fixity of retail lettuce prices, while Slade (1998) shows the same in a dynamic model of price behavior by retailers selling wheat crackers. Explanations for price fixity, however, go far beyond these "menu cost" rationales and, in fact, go to the heart of what we see as the source of imperfect competition in the retail grocery industry.

In the past, macroeconomists used the notion of costly price adjustments (menu costs) to explain aggregate price rigidity in inflationary environments. However, they now recognize that there are many potential explanations. In fact, Blinder et al. surveyed firms in several different industries in order to find which explanations are the most common in an empirical sense. Among the many potential explanations for price rigidity, only a few were found to be relevant to firms engaged in retail trade. By far, the most common response by firms of all types in the survey, and particularly those in retail trade, is that sticky prices are caused by a "failure to coordinate," in the words of Ball and Romer. This explanation, which Ball and Romer attribute to the notion of "strategic complemen-

[4] Bernard and Willett's general terminology of affected and causal prices is appropriate as there is some question as to the locus of price determination in many industries.

tarity" developed by Cooper and John, recognizes that rivals respond to one another's price increases by increasing their own price. Once the competing firms reach a stable price, they are reluctant to move away from this equilibrium.

However, the question posed to survey respondents (Blinder et al.) reflects a concept more akin to Okun's notion of a kinked demand curve in that firms merely expressed a reluctance to be the first to raise prices for fear of losing market share, or to lower prices for fear of instigating a price war. If they could coordinate their price changes, clearly it would be optimal for them all to move together to a new desired price level. Although considered distinct explanations, this notion is very similar to the idea that prices are fixed by "implicit contracts" between a firm and its customers—maintaining relatively constant prices to loyal customers benefits firms through higher average prices that result from loyal customers' inelastic demand, but also benefits customers by allowing them to save on search costs. Still, these explanations ignore the fact that retailers interact with each other, and with their customers, repeatedly over time in a complex strategic way.

Following this line of reasoning, Mischel develops a conceptual model to show that sticky prices can be the result of a successful rather than a failed coordination in an environment where firms interact repeatedly over time. Indeed, the notion that strategic complementarity alone is responsible for price fixity is inconsistent with the price-reaction models of Gasmi et al. or Slade (1990). Ball and Romer's explanation is also at odds with other empirical research - based in econometric analysis of secondary price data rather than survey responses. In particular, the notion of coordination failure is inconsistent with Stiglitz's affirmation of Green and Porter's explanation for rigid or "fixed" prices in which oligopolistic firms enforce tacitly collusive price setting arrangements through punishment strategies based on the shared recognition of trigger prices.

When firms have complete, yet imperfect, information regarding their rivals' behavior, Green and Porter assume firms begin in a state of collusion, but punish rivals for a single-period defection from the (tacitly) agreed price by reverting to less profitable, noncooperative prices until rivals again fall in line and set the same, imperfectly competitive price (Friedman). If rivals are aware of each other's strategies and are sufficiently patient, then such a tacit cartel can survive threats to "cheat" and undercut the agreed price again.[5]

When information is less than perfect, however, a firm does not know whether a low price (in the case of output market rivalry) represents a defection by a rival or simply results from adverse market conditions. Employing the harsh punishment strategy envisioned by Friedman results in a step-like pattern of behavior, with prices varying between low, noncooperative levels and somewhat less than the perfectly collusive level.6 This explanation, while not originally intended as a rationale for fixed prices, has found empirical support in 19th century railroads (Porter (1994), Lee and Porter, Hajivassiliou), the airline industry (Brander and Zhang), beef packing (Koontz et al.) and processing potatoes (Richards et al.). If this explanation is correct, then fixed prices may be a direct artifact of strategic behavior in imperfectly competitive industries. On the other hand, fixed prices are also consistent with many models of competitive pricing behavior, whether in response to the high cost of physically changing prices (Slade), not wanting to cause confusion among consumers (Bils), constant selling costs (Blinder et al.), or the possibility that consumers become very price sensitive during recessions (Rotemberg and Saloner). Whether price fixity forms the basis for a more complete model of fresh produce pricing by retailers—both upstream to their suppliers and downstream to their customers—depends upon whether its predictions are consistent with the price data from our sample commodities and markets.

Summary of Preliminary Data Analysis

While we leave an extended discussion of the econometric methods used to analyze the fresh produce data elsewhere (Richards and Patterson, 2001), we summarize our results here before moving to the central issue of the behavior of fresh fruit margins. Essentially, we find that: (1) fresh fruit prices tend to be formed at the shipping point rather than at retail; (2) retail price adjustment in response to a shock at the shipping point is fundamentally asymmetrical, with retail price

[5] This is by no means the only effective punishment strategy. Abreu et al. show that, in a more general model than Green and Porter, optimal punishments are less benign than a reversion to Nash strategies and can last for only a single period.

[6] Green and Porter develop their model assuming Cournot rivalry, while Porter (1983) considers the same example from a Bertrand perspective. As Porter notes, the models differ very little.

increases occurring far more rapidly and completely than price reductions; and (3) retail prices, while not fixed in an absolute sense, appear to be relatively stable compared to shipping-point prices.

Despite this study's concern with a broad set of commodities (apples, fresh oranges, fresh grapes, and fresh grapefruit), it is necessary to direct the analysis to a more specific set of goods in order to avoid problems of aggregation across products that may be viewed as imperfect substitutes by consumers.[7] Consequently, our data consist of retail and shipping-point prices for Red Delicious apples (Washington FOB prices), fresh oranges (California FOB prices), green seedless grapes (California Thompson and Perlette varieties), and fresh Florida grapefruit. The retail scanner data are from a private data vendor and include the weekly average price and total quantity sold from several grocery chains in six regional markets. Further details of these data are reported in the data description section below, but we describe the specific results on an issue-by-issue basis here.

First, for each product, we find that shipping-point prices "cause" retail prices. In other words, our statistical models show that variation in shipping-point prices explains subsequent changes in retail prices, but there is no evidence that the opposite occurs as well. This implies that the locus of price discovery is apparently at the grower or shipper level—a result that is consistent with much of the prior research discussed above regarding the commodity price discovery process. When the locus of price discovery is at the shipping point, as in our case, this means that expectations of future supply and demand conditions are largely formed at the source of the commodity. It does not mean, however, that only supply conditions cause prices to change. Rather, it may mean that retailers set their buying prices based on their expectations of retail demand and their observations on supply conditions. Further, due to the geographic isolation of many markets for farm products, the fact that prices are determined at the source of the product does not imply that these changes occur instantaneously, nor are they likely to occur at the same rate for price increases and decreases. What remains to be determined is the extent and speed with which these price changes are transmitted from shipping point to retail.

Second, we find considerable, but variable, evidence of asymmetry in price adjustment. For this test, we divide the data into periods of rising and falling prices and, accounting for other factors that may explain the process of price adjustment, estimate the rate at which prices return to their ideal levels in each regime. In this case, the results are mixed across commodities. While we are very confident, in a statistical sense, that prices adjust at different rates, depending on whether they are rising or falling, for grapes, oranges, and grapefruit, we are less certain of this finding for apples. However, we are more certain of our finding that retail prices do not adjust instantaneously for any commodity. The fact that prices do not adjust immediately in response to changes in market fundamentals is perhaps not surprising, however, and is not necessarily due to any imperfection in the price transmission process. Rather, if prices are costly to adjust, or are fixed by contract or consumer expectations, then we would expect to observe prices that are relatively constant.

Asymmetry in price adjustment is often viewed as less innocuous. In fact, if retailers are intent on profiting from price volatility, then we would expect to observe retail prices responding more quickly to a rise in shipping-point prices than to a fall. This is exactly what we find. Specifically, a rise in grape shipping-point prices causes retail prices in the subsequent week to rise only 63 percent of the original price increase. On the other hand, only 54 percent of a fall in grape shipping-point prices is passed through to retail in the first week. Although this difference may appear to be small, it does mean that retailers are relatively quick to pass along cost increases to consumers compared with price reductions. This result implies that retail grape prices take approximately 1.5 weeks to completely adjust to a rise in shipping-point prices, but adjust completely to a fall in shipping-point prices after approximately 2 weeks.

Among other commodities, apples and oranges exhibit significantly asymmetric price adjustment, but the difference between upward and downward adjustment rates is smaller for oranges than it is for apples. Retail orange prices also appear to adjust more rapidly than either apples or grapes, while grapefruit prices adjust

[7] Nonetheless, some product aggregation was inevitable due to the lack of specific shipping-point price data on fruit of a particular size, grade, or source description. While existing USDA - AMS price data do indeed cover a range of sizes and varieties for many fruits, these were deemed inadequate due to holes in reporting periods, reports of biases in the price gathering procedure, wide ranges between the high and low price quotes for a given week, and their seeming fixity despite evidence from other sources to the contrary. Therefore, FOB price data were obtained from each of the relevant commodity commissions or grower-sponsored price reporting agencies.

the slowest of all. Further, all adjustment rates fall in the quantity moving to market each week—a result that is consistent with either adjustment costs that rise in the amount sold, or an increase in market power during periods of oversupply.

Third, we find that retail prices are sticky relative to shipping-point prices. Similar to the empirical approach adopted by Slade (1998) for this purpose, we construct a simple statistical model that is intended to explain the probability of a change in retail prices (where a change is defined by a movement of more than $0.01) as a result of changes in shipping-point prices. As expected, we find that the likelihood of a change in the retail price is unrelated to changes in shipping-point prices. Thus, as a first approximation, we can conclude that retail prices are fixed in the face of fluctuations in underlying supply and demand for the product. Consequently, growers are likely to be worse off because demand for their output is not allowed to respond to changes at the consumer level.

Although these preliminary empirical results, taken together, seem to imply that retailers do enjoy a certain measure of control over the determination of shipping-point prices, the extent to which prices deviate from purely competitive levels requires a more detailed analysis of price behavior. Specifically, we must account for variations in commodity supply, retailing costs, consumer demand and strategic behavior by rival retailers if we are to gain a better understanding of fluctuations in retail margins. Of these factors affecting retail margins, the potential for strategic behavior is perhaps the most difficult, yet important, to identify.

Fundamental Question: Do Retailers Have Market Power?

Rivalry in Semi-Perishable Produce Markets

Sweeping generalizations of how buying and selling prices are determined in produce markets are invalid if not impossible. Each fruit and vegetable market is distinct. However, to be useful, economic models of price determination must separate which market differences are important from those that may be plausibly assumed to be constant. The commodity markets considered here are all semi-perishable—each can be stored either on the tree or in cold storage for a significant amount of time.

Other studies concerning produce price determination explicitly consider the extreme perishability of fresh farm products (Sexton and Zhang). In cases of extreme perishability, supply is fixed when price is above marginal harvesting costs, but supply falls to zero for prices below the cost of harvesting. When prices make harvesting feasible, any surplus returns above the cost of harvesting are divided among buyers and sellers according to their relative bargaining power in the market, which is largely influenced by the amount of supply. If the product is storable for a significant amount of time (grapes, apples, oranges, or grapefruit) or is manufactured (bagged salads), this type of pricing mechanism does not apply. However, it is still true that the grower price for nonmanufactured fresh fruits is likely influenced by the relative bargaining power of retail buyers on one side and grower-shippers on the other. Given that growers are often separated by large distances and do not have a history of effective coordination, retail buyers are more likely able to set prices.

As such, retail industry members must consider how each rival uses their own power in setting prices to growers. Given the relative inelasticity of supply at any point in time, and the fact that category management and efficient consumer response methods rely on using price as a strategic tool, it is more likely that this rivalry takes the form of competing on offered prices on both the buying and selling sides rather than on quantities purchased. Similarly, these same buyers often interact in common retail markets as produce sellers. With the amounts that they sell determined by their buyers often weeks ahead of time, amounts that are in turn determined by the prices paid to growers, rivalry at this stage is again in prices rather than quantities. This assumption is supported by survey evidence that finds almost 70 percent of produce sellers set prices according to their rivals' behavior (McLaughlin et al.). However, this simple model of retailer interaction considers only their single-period or static rivalry. Reality is far more complex and dynamic, with rivals learning from one another and revising strategies to allow for cooperation and mutual benefit.

An Economic Model of Strategic Pricing Among Retailers

The fact that retail produce prices remain fixed for long periods of time, despite wide swings in shipping-point prices, supports Stiglitz's notion that retail price fixity derives from a fundamental success in coordination among retailers, rather than a failure as suggested by Ball and Romer. Indeed, arguments that retailers cannot possibly share information efficiently enough to support an implicitly cooperative outcome similar to that described by Green and Porter fail to recognize the popularity of "food pages" in the weekend paper, the proximity of retail grocery stores within U.S. cities, and the fact that most metropolitan areas are effectively served by only three or four major chains. Clearly, to sustain noncompetitive pricing, there must be some means by which rivals do not formally cooperate with one another to fix prices.

By interacting on a daily basis, the repeated nature of rival firms' decisions can lead to tacit, or implicit, coordination. Moreover, other studies explain similar price patterns that we observe here as resulting from factors unrelated to market power - consumer search costs (Bils; Lal and Matutes), fixed or "menu costs" of price adjustment (Slade 1998; Sheshinski and Weiss) or simply cyclical fluctuations in supply and demand (Rotemberg and Saloner; Warner and Barsky; Sexton and Zhang). Indeed, ours is but one among several explanations of observed price patterns in the retail produce industry.

There is a large body of research that attempts to explain price wars as outcomes arising from repeated interactions between firms. Slade (1990) categorizes these theories into three groups: learning models where firms use price wars to cause rivals to reveal their costs (Slade, 1987), cyclical models wherein the strength of industry demand influences the incentives to cooperate or not (Rotemberg and Saloner; Haltiwanger and Harrington; Hajivisilliou), or "imperfect monitoring" models (Green and Porter; Abreu et al.). Because the grocery industry is relatively stable, its members often next to one another in shared markets, and capable of only imperfect competitive monitoring due to the multi-product nature of their format permits, it is clear that the "trigger price" model is the most plausible.

Using the logic of Green and Porter and Porter (1983), Lee and Porter explain the episodic price wars engendered by the Joint Executive Committee (JEC) in the U.S. rail industry of the late 1800s. Porter (1983), however, assumes that the punishment strategy is carried out in quantities, much like dumping product on the market to lower prices, while Brander and Zhang allow for either price cutting or dumping supply on the market. Using firm-specific data on duopoly airline routes, Brander and Zhang find considerable support for this type of trigger model in quantity. Koontz et al. find support for a trigger price specification in the U.S. meat packing industry - an industry with supply conditions very similar to what we see in fresh produce. Further, Hajivassiliou, using the JEC data, tests a trigger price model against one in which behavior is explained by cyclical changes in demand and rejects the latter, but can not reject the implications of the former.

Consequently, there is considerable empirical support for imperfect monitoring models in general, but less for other dynamic oligopoly models. More important, the way in which fresh produce is bought and sold is highly conducive to the type of information flow required for an imperfect monitoring model to function. First, imperfect price signals are likely to exist in relatively thin markets, such as the market for fresh produce, because buyers deal with hundreds of suppliers where formal price announcements are logistically impossible (Koontz et al.). Second, most markets are seasonal so buyers are likely to interact with different sellers at various times during the year. Third, the supply facing one retail buyer is likely to be influenced by both rival behavior and the inherent randomness of supply. Finally, retail buyers form a small group within each region, so they can easily share information among each other (implicitly) through negotiations with large sellers or selling groups. Ultimately, however, the true test of which model is most appropriate is found in the data itself.

Our description of the imperfect monitoring model should make it clear that, although the best outcome from the perspective of buyers is to cooperate in all periods, thus earning a share of monopoly profits throughout, this is not a realistic description of what we observe given the uncertainty inherent in market prices and rivals' strategies. Rather, it is more likely that retail produce buyers, if they are able to tacitly cooperate with each other, do so by cooperating when market prices are clearly in their favor. They respond to cheating on this "agreement" with punishments that take the form of competitive pricing (Green and Porter; Porter (1983); Koontz et al.). Such punishments are likely expected by other firms in the industry because cheating cannot be tolerated by firms interested in making the most profit possible year after year in bargaining with the same set of suppliers.

Implications of Dynamic Model of Rivalry

Retailers' adherence to fixed-price policies form a key part of any category management program. We argue here that they also facilitate tacit cooperation among their rivals in both their buying and selling activities. In terms of the prices that are observed in raw product and retail markets, the prediction of this model is that retail prices will vary over time, alternating between regimes of punishment and cooperation among retailers. During cooperative periods, prices are bound between a competitive level and a monopolistic one depending upon the extent to which rivals are able to effectively agree on a common price. When the industry is undergoing punishment, however, margins will reflect buying prices bound between the competitive level and somewhat above pure monopsony in the extreme. On the buying side, firms are assumed to punish their rivals by periodically paying a relatively high price when profits in the previous period fall below some trigger level. However, they cooperate with their rivals when profits are above the trigger. Together, these two regimes constitute a pricing strategy, wherein high shipper prices are maintained only long enough to restore the tacit agreement to set prices paid to growers.

Example of Discontinuous Behavior

Typically, evidence of such on-again, off-again behavior consists of periodic price wars (Slade ,1990; Brander and Zhang) or, in a more general model of rivalry with multiple tools, advertising campaigns (Slade 1995; Gasmi et al.). In the retail produce industry, however, rival grocers attempt to gain temporary market advantage, and thereby punish rivals, with periodic price promotions. In order to meet the increase in the quantity of produce demanded during these periods, retailers must pay shippers higher prices than would otherwise be the case. Therefore, we expect to observe falling profits during periods of aggressive price-promotion activity. Notice that a fall in profits during periods of relatively high volume is contrary to predictions of models of imperfect competition in perishable produce markets (Sexton and Zhang). These conflicting conclusions are not inconsistent with each other, however, as suppliers of "perfectly perishable" commodities are constrained by the amount of produce they have to sell and have little flexibility to increase or decrease supply during promotional periods. In order to test whether these predictions are consistent with our data on semi-perishable fruit sales and margins, we construct a statistical model that allows the extent of cooperation to vary with the amount of produce sold by retailers and, hence, sold by fruit suppliers. We describe the way in which we analyze the relevant fruit data next on a heuristic or intuitive level, and leave the formal development to a technical appendix.

Empirical Test of Imperfect Competition in Semi-Perishable Produce

Empirical Implications of Trigger Model of Tacit Collusion

Retailer margins are determined by both the prices they charge consumers and the prices they pay to shippers for their fresh produce. Therefore, in order to determine how much of the weekly variation in margins is due to the ability to set prices on either the buying or selling sides of the profit equation, and how much is due to simply market forces, we need to account for the factors that influence supply and demand. Further, by allowing both the raw product supply and retail demand curves to change slope, or pivot, we can estimate the extent to which variation in retailer-shipper margins depends upon retailers' use of the ability they may have to set prices (Bresnahan).

To accomplish this, we estimate equations representing: (1) produce supply, (2) retail demand, and (3) retailer margins. Besides changes in supply and demand, we also account for changes in retailers' costs - primarily labor used in stocking shelves and customer service, energy to heat and light stores, and business services such as insurance, real estate, and finance - so include measures of these costs in the margin equation. According to our conceptual model of retailer behavior, however, we also need to allow for the fact that rivals interact in different ways over time, alternately punishing or cooperating according to their assessment of rival behavior.

Data Analysis Method

The usual approach to estimating models of imperfect competition assumes that sample margins reflect a single set of firm strategies and market conditions. However, if retailers behave the way we believe they do, then margins should reflect alternating strategies - one in which retailers cooperate and the other in which they punish each other. The problem here is that we never know when they are cooperating and when they are punishing. Therefore, our estimation procedure is designed to estimate the probability of punishment or cooperation along with parameters that measure the degree of price-setting ability that may be inferred. Essentially, margin data are assumed to be produced by a *weighted average* of the two types of behavior that we expect to see in the real world. If this model is correct, then we should observe regimes in which retailers' prices in input and output markets are indistinguishable from those that we would observe in competition, and others in which they are clearly making cooperative profits. Identifying these regimes requires a large volume of very detailed pricing, sales volume, and cost data.

Sample Description

Unlike prior studies that employ this methodology in aggregate industry-level data, we estimate the effect of cooperative pricing on retailer-shipper produce margins using a sample of firm-level price, cost and shipment data. Further, to account for heterogeneity in regional produce markets, we estimate independent models for each chain and market in our sample. Specifically, the sample includes data for retail chains in Albany, Atlanta, Chicago, Dallas, Los Angeles, and Miami. For each chain, we have 104 weekly observations over the period January 1998 to December 1999 consisting of price per pound and number of pounds sold from all stores of a given chain. For some commodities, however—most notably fresh oranges, grapefruit, and, to a lesser extent grapes—the sample does not consist of the full 104 weeks because we excluded weeks of no domestic U.S. shipments.

For each of our broad category definitions, we select a specific product as representative of the price dynamics of the entire category in order to control for aggregation errors over products of different quality, local supply, or local preferences. Specifically, the analysis concerns Washington Red Delicious apples, California green seedless grapes, California fresh Navel and Valencia oranges, and Florida grapefruit. Although our grape-product definition includes several different varieties, primarily Thompson seedless and Perlettes, this aggregation is necessary because there is no distinction between varieties drawn at retail. In the case of oranges, we combine Navels and Valencias due to the relatively short shipment season of each and the need to preserve as many observations as possible for the estimation of the model parameters. Initial estimates of an aggregate supply function show that the Navel and Valencia supply functions are similar after allowing for seasonality, so this variety aggregation is thought to be reasonable. Further, it is hoped that by comparing the results across commodities, chains, and markets, we will be able to provide some degree of qualitative evidence as to whether the use, or nonuse, of market power is typical of the produce industry in general or is specific to individual commodities, chains, or markets.

Data Sources and Data Description

All of our empirical results refer only to those companies from which we have sales volume and retail-price data. The list of participating companies depends, in turn, on those who are willing to share scanner data to a partner data-vendor. In this case, the source of all retail data is FreshLook Marketing of Chicago, Illinois. These data, commonly used for category management purposes by commodity commissions and large shippers, includes measures of: (1) weekly movements (quantity, in lbs.) of a given UPC or PLU coded product by chain and retail market; (2) listed selling price of the commodity by chain and market; and (3) number of stores within the chain selling the product. The exact definition of retail price used in estimation varies by commodity.

For apples, the price represents an average over all non-organic Red Delicious sales each week. Price differences between bagged and bulk apples were adjusted using the method suggested by Goldman and Grossman and applied to food demand analysis by Cox and Wohlgenant. In this way, we define a bulk-equivalent apple price for each market-chain-week observation. Although the retail price for individual apple varieties and sizes typically change very little over the sample period, it is necessary to aggregate this way in order to match our shipping-point price data, which do not differentiate among apples of the same variety beyond controlled versus regular storage.

For table grapes, the retail price is defined as the price reported for the particular green seedless variety sold in each market by each chain each week. Initial model estimates attempted to include sales from both Chilean and other offshore sources and U.S. sources in a complete, year-round model. However, efforts to estimate the supply response of imported grapes were unsuccessful, so we chose to focus instead on grapes of U.S. origin and a sample that represents only those weeks when U.S. grapes are sold. Within the class of “green seedless grapes,” there are not only several possible source regions, but many different varieties as well. Because the retail data do not consistently break out these varieties, however, we are forced to aggregate over all that meet this general definition. Fortunately, these varieties tend to overlap very little and represent relatively discrete parts of the sample period, so this retail price should correspond well to our shipping-point price. Further, all sales are random weight, so no correction between product forms is required. Fresh oranges, however, are sold in both bagged and bulk form, so a similar correction to that made for apples is also made in this case.

Although it would be preferable to focus on a particular variety of oranges, neither Navel nor Valencia oranges alone represent a marketing window of sufficient length to allow enough degrees of freedom to estimate the model. Therefore, we consider an aggregate “fresh orange” category consisting of both varieties. As in the grape case, the fact that the seasons for these varieties overlap very little serves to minimize errors induced by product aggregation. To further reduce the possibility of inducing such error into the model, we account for the different shipping seasons within our econometric procedure through a fixed-variety effects approach. Therefore, for each product we attempt to ensure that the calculated retailer-shipper margin represents actual market results and, as such, does not suffer from any external source of bias. For similar reasons, we combine red and white grapefruit prior to estimating the market structure models for these products. Further, we exclude those weeks in which domestic shipments were effectively zero—leaving 80 observations for each market. To explain variation in this margin, we estimate the cost of buying and marketing fruit using grower prices and price indices for the retailer cost function that we describe next.

Labor constitutes the major component of retailers’ costs. Wage data for workers in the retail grocery industry are from the Bureau of Labor Statistics *National Employment, Hours, and Earnings* report on a monthly basis for 1998 and 1999 (U.S. Department of Labor). This report also provides average weekly earnings for workers in the advertising, business services, and the FIRE (finance, insurance, and real estate) sector. These variables constitute our measures of input prices at the retail level. All monthly data are converted to weekly observations using a cubic spline procedure.

Marketing costs also include transport costs from the growing region to the destination market. For this, the USDA-AMS *Truck Rate Report* provides estimates of weekly trucking costs between a number of source and destination points for the sample of fresh produce considered here. Because the *Truck Rate Report* does not provide a consistent set of rates for all weeks in which there were positive shipments, numerous assumptions were made in developing continuous series for each commodity and market. In the case of grapes, weeks for which rates were not quoted were inferred from contemporaneous rates for lettuce and tomatoes for the same terminal market. Adjustments to the vegetable cost data were made based on the average differential for weeks in which both commodities were quoted for a similar source-destination pair. This procedure was also used for periods in which orange transport data were not reported.

Estimating the supply curve for fresh produce requires data on farm input prices, primarily associated with harvest, and prices of alternative uses for each fresh commodity. In each case, the output price is defined as the shipping-point price paid at the source on a free-on-board (FOB) basis. Any difference between this and the farm-gate price is due to grading and packing charges levied on the grower by the shipper. For Washington apples, the price represents a weekly average over all sizes and grades of Red Delicious apple as reported by the Washington Growers' Clearing House. Because the proportion of regular-storage and cold-storage apples that are shipped varies each week, the price is simply a weighted average of each type. To estimate the extent of any rotation in the supply curve (i.e., non-parallel shifts required to identify the market power parameter), this price is multiplied by the harvesting wage that is relevant to each product. For apples, this is the average wage of harvest workers in Washington State, which is obtained from the Washington State Employment Security Department's *Labor Market Information* report. Similar data for California are used for table grapes and fresh oranges and for Florida in the fresh grapefruit model and are obtained from the USDA-NASS *Farm Labor* publication.

Commodity price and output data are either from the appropriate commodity organization or from USDA-AMS sources. Specifically, shipping-point prices for regular and cold-stored Red Delicious apples are from internal reports generated by officials at the Washington Growers' Clearing House. These reports also provide monthly shipments for both types of apples to all domestic destinations. For table grapes, similar price data are from the California Table Grape Commission, while shipments are from the USDA-AMS *Shipment Report*. For purposes of this research, shipments were defined to include only those from domestic U.S. sources. As mentioned above, periods during which the U.S. market was supplied from Chilean or other import sources are excluded from the analysis. This is also true for fresh oranges and grapefruit as the period of analysis includes only those weeks in which U.S. fruit was sold through retail markets. For all fresh citrus, both the shipping-point price and shipment data are from the USDA-AMS. Although these shipping-point data include prices for a range of sizes, the retail data do not, so we construct an aggregate consisting of a simple average price per week. Implicitly, therefore, this procedure assumes a uniform distribution of shipments by size. Finally, all prices are converted to dollars per pound in order to compare directly to the retail price data.

To test the hypothesis that retailers' ability to set price falls with the amount of weekly shipments, we allow a parameter that measures the degree of market power in each model to vary with total weekly shipments of each commodity. These data were obtained directly from USDA-AMS officials and include all shipments either to or within the U.S. on a weekly basis. Therefore, we include imports to the U.S., but exclude U.S. exports abroad.

Although it would have been preferable to allow each conduct parameter to vary with some indicator of industry structure such as the level of concentration or a non-endogenous measure such as any non-strategic entry barriers, high-frequency data are not available for any of these variables. Therefore, we are left to infer any change in the ability to price strategically from our parameter estimates and observed trends among retailers in each market. Despite these limitations, however, we are confident that the data described here provide the most detailed picture of fresh produce market behavior currently available.

Interpretation of the Empirical Results

Market Power in Grower and Retail Markets

As we emphasize in developing our method of analysis, the ability of any approach to separate the use of market power from changes in supply or demand relies upon an accurate accounting for all other factors that may contribute to variation in both grower and retail prices. However, despite the fact that we do estimate models of demand and supply for each commodity, the specific results of these models is not of central interest here, so they are reported in the technical appendix and fully discussed elsewhere (Richards and Patterson, 2001). This section, therefore, provides an explanation and interpretation of our empirical results specifically as they relate to the cooperative price setting behavior by retailers in commodity and retail produce markets. In order to preserve the anonymity of individual retail chains, we present our results in terms of average indices of pricing or market power for each of the six regional markets, for each commodity.

Perhaps more important than these individual index estimates, however, are estimates of the impact of market volume on retailers' price setting ability. Rather than simply describe symptoms of any behavioral problems that may exist in retail produce markets, these estimates provide critical insights into their underlying cause. Specifically, we are able to assess whether or not retailers possess a critical facilitating mechanism through which they may be able to tacitly cooperate to set imperfectly competitive prices. In doing so, we interpret the results commodity by commodity, beginning with Washington Red Delicious apples.

Washington Apples

Prior to interpreting the specific results of our statistical tests on the ability of retailers to set prices, we must first establish the legitimacy of our overall approach. To do so, we conduct tests of whether or not the retail-farm margin data are consistent with a world in which market rivals go through periods of cooperation with one another followed by periods of punishment by reversion to more competitive pricing. Although no statistical tests can claim to provide entirely conclusive results, we find strong statistical evidence in support of our view of how retailers set buying and selling prices for apples. Specifically, we find that margins appear to follow a pattern wherein they fall into either of two regimes—one where they are relatively narrow, where growers or consumers receive competitive prices, and others in which they widen significantly, where growers or consumers face noncompetitive prices. This pattern could arise under a number of different circumstances, but it is very plausibly explained by our theory of retailer pricing behavior.

Perhaps stronger support for this theory lies in the impact of apple sales volume on the index of market power. According to our hypothesis, observed pricing power by retailers should fall with sales volume due to their need to secure sufficient supply to meet higher quantities demanded under periodic price-promotion programs. Our statistical evidence is not as strong on this point, but we do find this effect in a majority of our retailer/market pairs. Clearly, because there is some diversity in marketing strategies among major retailers, there are some that do not follow this generic pricing strategy. For example, it is well known that one major retailer follows instead an everyday low price (EDLP) strategy, irrespective of its rivals' pricing behavior. Perhaps for this reason, it is clear that the ability to price strategically is not uniform across markets.

Apple Commodity Market

While non-uniform, there does appear to be a relatively consistent pattern of price setting power in both commodity and retail markets that is, in many cases, significant both in an economic and in a statistical sense. Specifically, in Albany we find that retailers, on average, exercise a significant degree of power in both their buying and selling activities. Given that the scale of this index is bound between zero (competitive pricing)[8] and one (perfect pricing coordination) on the buying side and zero and the number of sellers, N, on the selling side, the degree of buying power is considerably higher than what we would observe in perfect competition.[9]

The index of commodity buyer market power varies from 0.144 in Dallas to 0.765 in Los Angeles (fig. 1). (The technical appendix reports all the estimated parameters for each region and chain). Interpreted purely as an

[8] Technically, this index approaches $1/N$ at the lower bound, where N is the number of retail buyers; this clearly goes to zero as N becomes large.

[9] This range applies to the absolute value, or ignoring negative signs, for the estimated index. The figures present negative values for buying-power indices for illustrative purposes only.

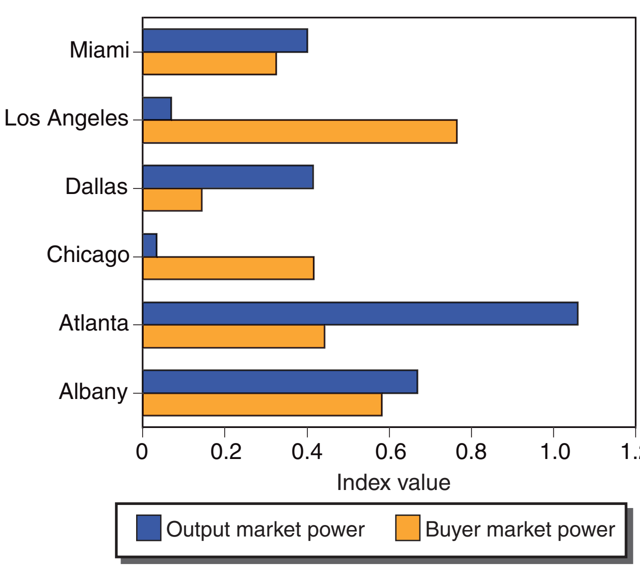
index, the degree of buying power exercised by retailers in the apple market appears to be only moderate, averaging 0.446 over all sample markets. This means that fully 44 percent of the difference between retail and shipping-point prices is explained by buying power - certainly not perfectly cooperative levels of distortion, but not consistent with perfect competition either. These results are not statistical anomalies as 80 percent (32/40) of the index values estimated for individual markets are "statistically significant."

Careful readers may also wonder how individual retailers, or retailers in different markets for that matter, can possibly have different levels of buying power? Remember that buying and selling prices are inextricably linked in a retailer's overall business strategy. To carry out a seasonal or periodic promotion campaign for a particular produce item, a chain, a regional office, or a group of stores must arrange to acquire more than they would otherwise typically buy. To do so, they must either raise the price that they are willing to pay, or go to other suppliers that they do not typically use. Either way, their degree of leverage is lower than usual.

This observation is also consistent with the distribution of buying staff within retail chains. If all buying were centralized, we would expect no difference among regional markets. However, McLaughlin et al. (1999) report that 30 percent of buyers are located at corporate headquarters, 45 percent in regional branches, and

Figure 1

Washington Red Delicious apple market power indices, 1998-99



Source: Economic Research Service, USDA.

25 percent in the field so 70 percent of all acquisitions originate either in regional or field offices. In summary, though the exercise of buying power in the apple procurement market is consistent and pervasive, it is often only moderately imposed.

Apple Retail Markets

In general, our results lend support to the notion of buyer collusion; firms will use similar strategies if it is tacitly recognized that this is in their shared best interests. There is, however, a considerable range in conduct parameters both within and across some of the other markets. In retail apple markets, or the consumer side of the market, the pricing index varies from 0.033 to 1.058, again interpreted in absolute value. In this case, however, the low value (the Chicago market) is an anomaly as the mean index value is 0.441 (fig. 1). Excluding this result, it is apparent that retailers exercise a greater degree of power in setting selling as opposed to buying prices. Without Chicago, over 50 percent of the retail-farm margin is due to imperfect competition. While there appears to be little effective cooperation in setting retail prices in Chicago or Los Angles, the opposite is true in Atlanta. Overall, however, only 2 of 20 parameters are not significantly different from zero, so we can conclude with some confidence that tacit cooperative pricing behavior is a least fairly typical among retail supermarket chains. There appears to be little relationship between market structure and the ability to set price. Much of the concern surrounding the recent wave of retail mergers focuses on this connection between structure and conduct - the belief that markets dominated by a few, large firms provide the participants more incentive and a greater ability to collude both against consumer and supplier interests. However, the most competitive output markets are also the ones generally served by fewer retailers—Chicago (four-firm concentration ratio (CR4) of 81.6 percent in 1998 according to VNU Marketing Information *Marketscope*) and Los Angeles (CR4 = 76.4 percent). Indeed, the market dominated by the fewest retailers, Miami (CR4 = 88.2 percent), appears to be only moderately collusive and, at any rate, very similar in this respect to other markets served by more retailers. The results from our empirical model also provide other evidence of the likelihood that firms will use their ability to price strategically.

Probability of Collusion

Specifically, our model estimates the proportion of weeks during which each retailer can be described as either “cooperative” or “punishing.” In the Albany market, for example, one chain cooperates 65 percent of the time, whereas another cooperates during 47 percent of the sample weeks. Our expectation is that chains that are more likely to cooperate are those that exercise more power over price. However, this relationship appears to be quite loose in the case of apples. (This effect is more apparent in some of the other commodities.) Interpreting the probability of cooperation on its own terms, however, leads to a general conclusion that tacitly cooperative behavior in both commodity and retail markets is common, but far from perfectly coordinated in each sample period.

Consumers fare better under a market where firms engage in periodic price wars, if only to reestablish cooperation, than in a collusive market where prices, presumably, never change. This same conclusion applies to suppliers. In interpreting these results, these values do not suggest overt or conscious collusion during cooperative periods, but rather the tacit adherence to a pricing strategy whose intent is to restore order to what is perceived to be an unfavorable market.

Impact of Shipment Volumes

By modeling each pricing power index as a function of weekly shipments, we disaggregate the test for pricing power into two components: (1) a purely strategic element that captures how firms react to decisions taken by their rivals, and (2) the impact that shipment levels have on their ability to use their pricing power in commodity and retail markets. If the second component is positive, then this suggests that retailers’ bargaining power is enhanced through the mechanism described by Sexton and Zhang, namely that large supplies reduce the relative bargaining power of grower-shippers. If, however, the second part is negative, then this suggests that retailers have less bargaining power when market quantities are higher. In this case, the decline in retailer bargaining power is likely due to their pre-commitments to higher quantities during promotional periods and meeting retail demands created through their produce merchandising and category management programs.

In buying activities, we find this volume effect to be negative in 13 of the 20 chain-market pairs for apples and significantly so in 10 of these. On the other hand, this parameter is never significantly positive. Although we would expect the effect of shipments on negotiating power to vary by chain and market if the source of this effect is indeed in individual retailing strategies, the evidence support the hypothesis that higher volumes are associated with a loss of retail buyer power, not a gain. In the output market, a similar result obtains. Specifically, 14 of the 20 chain-market volume relationship are negative on the retail side, and 10 of these are statistically significant, while only 2 are significantly greater than zero. This result suggests that when a retailer commits to a large volume and buys produce accordingly, he or she loses pricing power on both the buying and selling side of the market.

Summary of Apple Market Results

Retailers do exercise power over price in both buying and selling activities apples. To the extent that this behavior causes the retail-shipping point margin to be wider than it would otherwise be, both consumers and producers incur losses as a result. Whether or not this is a general result, however, requires a similar analysis be performed with data from other commodity markets.

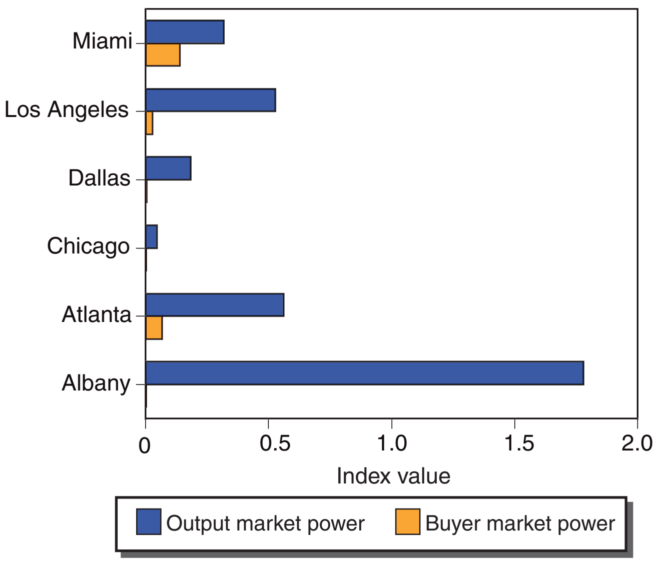
California Fresh Grapes

Due to the fact that the California grape season lasts only about 7 months, we estimate the statistical model using only 67 of the 104 weeks in our sample data set. Perhaps due to this, or the fact that some chains exhibited very little price variation at retail over the entire sample period, the model does not appear to fit the data as well as in the apple case. However, statistical tests still indicate that the trigger-price model is preferred to a static or single-regime alternative, so our approach is still preferred to the generally accepted alternative approach. On a market-by-market basis, however, the grape results are less plausible than in the apple case.

Grape Commodity Market

For grapes, 3 of the buying power indices and 2 of the output market power estimates are significantly less than zero. These estimates fall outside of the range permitted by the theory and imply that margins actually fall (either retail prices are lower or grower prices are higher) due to the strategic behavior of rival retail chains. This is not a plausible result. With this caveat in mind, however, most other markets and chains provide estimates that are plausible, and somewhat consistent with the apple results. In particular, the input market (buying) conduct parameter is statistically greater than zero in 10 of the 20 sample chain / market pairs and averages 0.040 over the entire sample (fig. 2). Miami retailers appear to exercise the most signifi-

Figure 2
California fresh table grape market power indices, 1998-99



Source: Economic Research Service, USDA.

cant buyer power. However, in each case, the degree of power is considerably less than in the apple case and, in most instances, could be argued to be not significantly different from zero in an economic sense. Even in the Miami market, the conduct parameter ranges from 0.080 to 0.292, which is only slightly off the competitive standard. These results, therefore, suggest that retailers do not exercise a significant degree of buying power in purchasing seedless green grapes, insofar as pricing behavior is concerned.

Grape Retail Market

Among retail grape markets, the estimated average index ranges from a low of 0.045 in Chicago to 1.781 in Albany, and averages 0.569 over the entire sample (fig. 2), suggesting that most of the difference between retailer and shipper prices is due to retail pricing activity in Albany. The estimate for the Albany market is suggestive of cooperative behavior, which is observed much of the time. Chains within the Atlanta and Miami markets tend to be relatively consistent in their ability to set price, whereas Los Angeles presents somewhat of an enigma. Although two chains in this market can be described as relatively cooperative in their behavior, the other two are very nearly competitive. This result is instructive, as it argues against painting all retailers with the same brush with respect to their pricing and other strategic activities. Except for one retailer, the Dallas market appears to be fairly competitive in both buying and selling fresh grapes.

Impact of Shipment Volumes

Because grapes are more perishable than the rest of our semi-storable fruits, we expect higher shipment levels to lead to higher degrees of bargaining power for retailers relative to suppliers. This would imply a significant positive parameter in the conduct parameter functions. In fact, of the 11 parameters that are statistically different from zero on the input side, 7 of these are positive. Although this evidence is not conclusive, it is suggestive that this volume effect is more prevalent than with apples. Further, of the significantly negative parameters, none are large in an economic sense.

In the output market, we hypothesize that higher levels of output are largely due to unobservable, nonprice promotion efforts such as newspapers or other store-level ads. For a given level of supply, consumers are more sensitive to price in these instances and retailers must refrain from charging a higher price. Again, this suggests a negative value for the impact of sales volumes on pricing power. From the chain-by-chain results, this occurs 9 times out of 20 and 5 of these relationship are statistically significant. Therefore, these results provide only weak support for this hypothesis.

California Fresh Oranges

For fresh oranges, we initially sought to focus only on Navel oranges in order to minimize the degree of product aggregation error that is inevitably induced in models of this type. However, the freeze of December 1998 and the seasonality of orange production meant that this focus would leave very few observations over our relatively short, 2 year time frame. Therefore, we estimate the fresh orange market power model and each of its components (supply and demand curves) with a fresh orange composite product, consisting of Navel oranges during the first part of each year and Valencia oranges for the remainder. We account for fundamental differences in these products by allowing for seasonal variation in all model components.

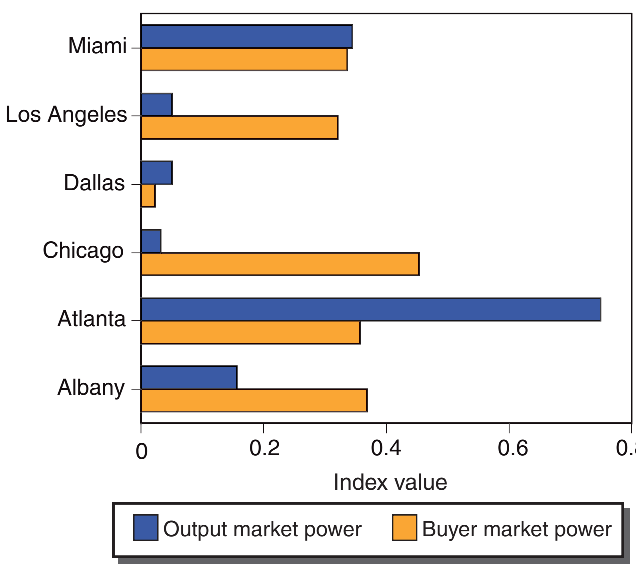
Including only the weeks in which fresh oranges are shipped from U.S. sources, figure 3 shows the results from using 87 weekly observations over the 1998-99 calendar years. Again, statistical tests of the trigger-price model suggest that it is preferred to the "static" alternative for each chain in every market. Thus, each chain experiences periods in which prices at both retail and the shipper level are set such that the retail-shipping point margin is at relatively cooperative levels, and other periods in which margins are set more competitively.

Orange Commodity and Retail Markets

Retailers in the fresh orange market appear more likely to cooperate in consumer (output) rather than in input (buyer) markets. Whereas only 8 of 20 chains appear to use considerable leverage in setting prices for raw oranges from shippers, 15 chains set significantly noncompetitive retail prices - significant, that is, in a statistical sense. With respect to the retail market, the average pricing index is 0.231 and ranges from 0.032 in Chicago to 0.750 in Atlanta (fig.3). The deviation from purely competitive pricing appears to be significant in an economic sense, as well. On the input side, the extent of deviation from competitive pricing appears to be far greater than in the grape case, and similar to apples. The commodity pricing index is 0.310 for oranges, suggesting that retailer-shipper margins are roughly 30 percent wider than they would otherwise be (fig. 3). (This average is somewhat skewed by the Dallas market result, where retailers appear to possess very little ability to set price.)

It is tempting to look toward Sunkist and a few other large independent packing houses as effective countervailing forces in this market. Whereas growers of the previous two commodities (apples and grapes) tend to either sell alone, go through an independent packing shed, or form some sort of marketing alliance, fresh orange growers are more likely to belong to an organized cooperative or to supply a large, independent packing house. Therefore, with more effective supply coordination by growers, it is more difficult for retailers to exert any buying power.

Figure 3
California fresh orange market power indices, 1998-99



Source: Economic Research Service, USDA.

Impact of Sales Volume

Retailers that fail to secure sufficient quantities of fruit prior to a promotion will more likely scurry to meet demand at the last minute, thereby paying higher prices. In the output, or retail market, however, a negative relationship between sales volume and market power may also arise as promotional periods could be viewed by rivals as violations of the tacit market-sharing agreement, providing just cause for a round of punishing loss-leadership or price wars. As with table grapes, however, the orange results are mixed on this point. Only 8 of 20 chains experience a reduction in buyer power as a result of higher quantities going to market, while only 2 of 20 undergo the same effect in the output market.

Again, it is tempting to posit explanations from the trading institutions particular to this industry. Namely, the more control over supply growers and shippers have, the less likely the use of buying power as decision over the quantity shipped is more the shipper's than the retailer's. Furthermore, there is very little support for the theory that retailers' bargaining power rises with the total amount marketed of each fruit.

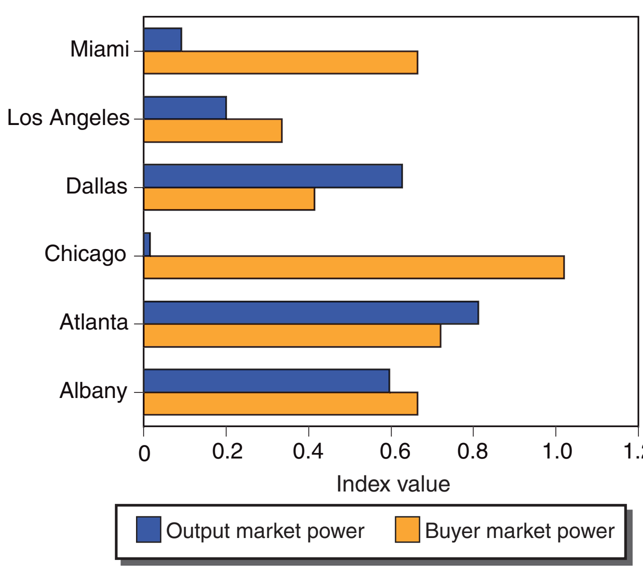
Florida Fresh Grapefruit

As with fresh oranges, grapefruit data represent a potentially heterogeneous product as different seasonal arrangements fill store shelves throughout the year. Moreover, grapefruit shipment data consist of both red and white varieties, each from a different growing region and slightly different growing season. Once again, in order to construct a reasonably continuous data set of grapefruit shipments, we define fresh grapefruits as an aggregate of both reds and whites. However, we exclude months of zero domestic shipments from the model. This avoids potential complications related to world grapefruit shipments handled by Florida shippers. In general, June, July, and August are the only months in which domestic shipments fall to zero and retailers must rely on imported product. Because consumers are able to source imported grapefruit over these months, however, we include all months in the retail model and account for any seasonal differences in demand accordingly.

Grapefruit Commodity and Retail Markets

Our analysis supports the assertion that retailers use periods of price promotion to reinforce cooperation around commonly agreed prices in two ways. First, as with other commodities, a two-regime model that describes retailers as behaving according to a trigger-price strategy does a far better job of explaining the data than a model without this feature. When there are few buyers (retailers) that sell the bulk of fresh grapefruit to consumers, (and buy from shippers), our results are highly suggestive of collusive behavior on the part of retailers. Second, strong statistical results suggest that periods of punishment occur roughly one-quarter of the time for most chains—approximately the amount of time between promotional periods. Intermittent promotions, in turn, are the mechanisms through which retailers punish, given common retailing practices that we observe for fresh produce. Our empirical analysis of the grapefruit data again indicates how close observed prices are to the "competitive ideal" in both input and output markets. Buyer power clearly exists in the majority of our sample markets (fig. 4). In fact, 12 out of 20 chain-market pairs exhibit statistically significant deviations from competitive pricing and, of these, nearly all are economically significant. Indeed, the mean pricing index on the buying side ranges from 0.330 in Los Angeles to 1.020 in Chicago, suggesting that grapefruit growers are not being paid full value for their produce. In terms of shipping-point prices, this latter result implies that prices are (almost) fully collusive in Chicago.

Figure 4
Florida fresh grapefruit market power indices, 1998-99



Source: Economic Research Service, USDA.

Although the emergence of national, centralized buying offices for the major chains may lead to an expectation that buying power is likely to be exercised upstream, the data make a stronger case for pricing power downstream. In fact, all but two of the selling indices are positive and statistically significant, indicating some degree of price setting in retail markets. Although the degree of deviation from competitive pricing appears to be quite small in Los Angeles and Miami, prices in the Dallas and Atlanta markets appear to be highly noncompetitive. Whether this is due to tacit cooperative collusion, however, is another question.

Impact of Sales Volume

Again, our hypothesis on sales volume is supported if it is found that buyer power falls in proportion to the amount of grapefruit sold in any given week. In 13 of 20 cases, this is so. In fact, deviations from this pattern - in terms of significantly positive effects of volume on buying power—occur in only three chain-market pairs and even then the estimated parameter is very small. The evidence is less strong on the output-market side as only 11 chain-market pairs exhibit significantly negative effects of volume on output market power, but again the positive parameters are uniformly very close to zero. Therefore, these results seem to bear witness that retailers' promoting of produce from time to time represents periods in which they exert less control over price in return for punishing rivals into subsequent cooperative behaviors.

Summary of Market Power Results

With respect to individual commodities, we find consistent and pervasive evidence of tacitly cooperative behavior and, hence, the exercise of buyer power for Washington Red Delicious apples. Although we cannot reject cooperative behavior among buyers of California green seedless grapes, their ability to suppress grower price does not appear to be significant in economic terms. Fresh oranges represent an intermediate case, with some retail chains demonstrating cooperative pricing practices in shipping-point markets and others not. For fresh grapefruit, the bulk of the evidence lies in support of buyer power, but there is no clear pattern among the sample markets.

In retail markets, we also find reasonably consistent evidence of imperfectly competitive pricing for apples, grapes, and grapefruit, although the extent of the deviation from perfect competition appears to be less for fresh oranges than for the other commodities. In the case of grapefruit, however, the pattern of imperfect pricing is both consistent and significant in terms of the extent of deviation from competitive pricing levels. For each of these commodities, however, there is considerable variation in price setting ability both among retailers and markets. Therefore, it is difficult to make a sweeping generalization as to the nature and extent of cooperative behavior in the fresh produce industry as a whole.

Further, in the case of apples we find that retailer price setting ability tends to decline both in buying and selling when market volume is higher. This we attribute to retail strategies that commit sellers to higher volumes during promotional periods, requiring them to either obtain favorable prices from suppliers or price more aggressively in commodity markets at the time of the promotion. This result is not consistent across commodities, however, as we find that the opposite effect - of retailer bargaining power rising with market volumes - more likely to occur in the grape market. Our hypothesis on volume is strongly supported in fresh grapefruit. On the buying side, buyer bargaining power consistently falls with the amount of produce sold. Thus retailers may embrace periods of power over price as they promote fresh produce as a means of enforcing market discipline, thus tacitly enforcing cooperation in the amount of fruit bought from growers and, ultimately, sold to consumers.

Conclusions and Implications

This study represents a comprehensive analysis of pricing behavior in the fresh orange, table grape, fresh apple, and fresh grapefruit markets. For specific varieties of each commodity, we investigate issues including the locus of price determination, the symmetry of price transmission, the degree of retail price fixity, and the apparent control over price by fruit retailers in both output and input markets. Our data for this analysis consist of 2 years (1998 and 1999) of weekly retail-scanner price and sales data from six major metropolitan markets in various regions throughout the country. Within each market, most major retail chains are represented in the data. At the shipper level, our data consist of shipping-point prices and volumes obtained from either the USDA, or individual commodity commissions. These data are supplemented with data from a variety of other sources to account for transportation costs, marketing costs, and variations in factors that are critical to the demand or supply of each commodity. At each stage of our analysis, we apply econometric modeling techniques to these data that are widely accepted and acknowledged as appropriate for the particular purpose. While we are confident in the accuracy of our findings, they are, of course, conditional on the market conditions that prevailed during our particular period of study.

In order to gain an understanding of the behavior of prices in each market, we first determine where prices are determined within the marketing channel of each commodity. The results are consistent across all commodities—shipping-point prices cause retail prices, so we can conclude that prices are formed at the shipper level for all of the fresh fruits considered here. We also investigate the symmetry with which price changes at the shipping point are transmitted to retail price changes. For all commodities, we find that retail prices respond more rapidly to shipping-point price increases than decreases, although this result was less significant for apples than for the other commodities. This result is commonly interpreted as evidence, albeit indirect, of retailers' ability to extract some surplus from shippers when prices are volatile.

Retail prices not only adjust after and more slowly than shipping point prices, but we find that they are virtually fixed on statistical grounds. To maintain fixed prices in the face of volatile buying prices, a key feature of category management, a produce retailer must have some ability to control retail prices. Indeed, Slade (1999) shows that the extent of price fixity is likely to rise with strategic pricing behavior and shows that this is the case with store-level retail data. However, despite the fact that retail price fixity can cause losses at the grower level (Sexton et al.) due to imperfect transmission of price signals, it may also benefit the consumer due to greater price stability. Moreover, there are many explanations for fixed prices (menu costs, constant production costs, consumer search costs) that are entirely consistent with competitive behavior. Therefore, we require more conclusive evidence of imperfectly competitive pricing than this preliminary analysis provides. To that end, we develop a model of price determination at retail and wholesale that not only allows for a wide variety of retail and input-market pricing strategies, but also for explainable variations in supply and demand.

Specifically, our explanation for fresh fruit pricing is based on the logic of a "trigger-price" that has been shown to underpin cooperative agreements among 19th century railway companies, airlines in the 1990s, and present-day potato and beef processors. If tacit cooperative agreements exist among fresh fruit retailers who engage in day-to-day interaction in commodity and retail markets, then there must be some mechanism by which they are able to sustain the agreement among themselves to hold prices at a certain level. In the trigger-price model, this mechanism consists of a commonly understood price threshold. If an individual retailer believes that a rival is pricing below that threshold (above, in the input market) punishment ensues with a round of competitive pricing, often price discount meant to restore some market share lost to the cheating firm.

To determine whether this model is a good explanation for how prices are actually formed, we estimate a model that allows for separate regimes of cooperation and punishment and see if this does a better job of explaining the data than a simple, single-regime model. Applying this model to each of our commodities, we find evidence that these regimes do indeed exist and that pricing behavior within the cooperative regime may result in lower prices for growers and higher prices for consumers. However, these results vary considerably by commodity, market, and retail chain. For apples, we find evidence of both buyer and seller power that is both statistically and economically significant in virtually all market / chain pairs. For fresh grapes, we find a consistent pattern of output market power. Input market power is often statistically significant, but inconsequential in magnitude. Given the importance of grape imports, it is tempting to suggest that import competition causes this result, but we consider only the U.S. production season, in which imports play a minor role.

Retail orange prices also appear to reflect a considerable degree of price setting ability, but as in the grape case, the use of buyer power is less consistent and of a lower magnitude in most markets. For grapefruit, we find an irregular pattern of buying power—statistically and economically significant in approximately 60 percent of the market-chain pairs, but insignificant in the remainder of cases. On the other hand, grapefruit sellers consistently exercise a moderate level of market power in retail markets. For all commodities, periods of collusion occur roughly two-thirds of the time, so any benefit consumers or shippers may receive from periodic price wars is likely to be short-lived and unpredictable.

We also find some evidence that the degree of pricing power—whether in input our output markets—falls with the amount of volume in the system. This finding is in stark contrast to previous research showing that buyers of more perishable produce commodities (i.e., lettuce) tend to secure a greater share of the grower-retailer margin in years of relatively large supply, but tend to offer growers more competitive prices when supplies are tight (Sexton and Zhang). We believe that our result is due to the fact that retailers use periodic promotions of semi-perishable commodities as a facilitating mechanism for their cooperative behavior. By publishing prices that demonstrate their willingness and ability to reduce profits of other sellers, retailers are able to establish effective trigger levels in the absence of a formal mechanism of explicit collusion. During these periodic promotions, retailers "cheat" on the collusive arrangement and tend to price relatively competitively, only to return to the collusive pricing level once discipline is restored in the market.

This conclusion is supported by our estimates in several ways. First, finding that punishment regimes occur anywhere between one-third to one-fifth of the time is consistent with the frequency of price promotions in retailers' produce departments. Second, the fact that our statistical results show varying degrees of pricing power being exercised by different chains also supports this conclusion—some choose to behave as punishers while others tend to follow. Third, this result is also consistent with some retailers adopting an entirely different pricing strategy—instead of using the market power engendered by the collusive behavior to extract rents through the price mechanism, they choose instead to price competitively and then extract any rents through some other form of rent-shifting mechanism. However, a more complete study of this issue would compare estimates of retailer behavior, such as we do here, to measures of retail concentration using a longer time series data set that contains significant temporal and geographic variation in concentration.

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Technical Appendix

Appendix 1. Econometric Model of Tacit Collusion

Formally, assume a firm maximizes the present value of its expected future profits given an infinite series of input price strategies with the t element given by: wit.= sit (x0,x1,...,xt-1), so the objective function becomes:

$$V_I(\mathbf{s}_I) = \max_{si} E[\sum_{t=0}^{\infty} \beta^I \pi_I(\mathbf{s}_I, s_{-I})] \tag{1}$$

for a set of rival strategies $\boldsymbol{s}_{-i}$, a discount factor $\exists^t$, and input prices w_t. Further, assume that the observed price is the realization of a random market price variable subject to a multiplicative disturbance: $w_t = \psi_t w(\sum_i x_{it})$, where P are i.i.d with continuous density f and distribution function F. Under perfect information, rivals' actions are known with certainty and a collusive equilibrium can be supported if a punishment strategy is individually rational for all firms.[1] Individual rationality requires that the value of the firm under a collusive strategy be greater than the value of a single-period defection, followed by industry reversion to Bertrand prices:

$$V_I(w^i) > \pi_i\ (w^* + \beta^t V_i(z^i) \tag{2}$$

where w^i is the price a firm pays in "normal" or collusive periods, and z^i is the price in reversionary or Bertrand periods. Because information is assumed to be imperfect, however, the firm chooses between w^i and z^i based upon the only signal that can be observed – the market price. Consequently, a discontinuous pricing strategy results depending upon the relationship between market prices observed in the previous period and a trigger price $\overline{w}$:

$$w_{it} = \begin{bmatrix} w_{it}, & w_{t\text{-}1} > \overline{w}, \\ z_{it}, & w_{t\text{-}1} < \overline{w} \end{bmatrix}. \tag{3}$$

Stanford shows that such discontinuous strategies are necessary to support subgame perfect collusive equilibria except in the trivial case where continuous reactions specify replication of the Nash component game outcome.[2] However, within the class of discontinuous strategies, Porter (1985) argues that there are many possible equilibrium price and punishment-period length pairs, so it remains to describe the optimal strategy.

Defining the single-period profit during cooperative periods as $\pi_i\ (w_i)$ and that in reversionary periods as $\pi_i\ (z_i)$, the value of the firm initially in a cooperative period is given by the weighted average of the present value of profits from operating in each period:

$$V_i(w_i) = \pi_i(w_i) + \beta \Pr(\overline{w} < \psi w) V_i(w_i) + \Pr(\overline{w} \geq \psi w)[\sum_{t=1}^{T-1} \beta^t \pi_i(z_i) + \beta^T V_i(w_i)], \tag{4}$$

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[1] This is the Folk Theorem of Fudenberg and Maskin, the primary implication of which is that there is potentially many equilibria in a repeated game with discounting.

[2] Nevertheless, Slade (1987, 1990) develops a model wherein price wars are an equilibrium outcome of continuous dynamic reaction function strategies.

for reversionary periods of length T. Recognizing that$\Pr(\psi w_i < \overline{w}) = F(\overline{w} / w(w_i))$, (4) can be rewritten as:

$$V_i(w_i) = \frac{\pi_i(w_i) - \pi_i(z_i)}{1 - \beta + (\beta - \beta^T)F} + \frac{\pi_i(z_i)}{1 - \beta}, \tag{5}$$

which simply states that the expected present value of firm i is equal to the present value of setting prices at the Bertrand level forever, plus the discounted value of profit earned during collusive periods.

Maximizing the value of the firm, therefore, requires the following first order condition to hold:

$$V_i(w_i) = \pi_i'(w_i)[1 - \beta + (\beta - \beta^T)\mathrm{F}] + (\pi_i(w_i) - \pi_i(z_i))[(\beta - \beta^T)f(\partial F / \partial s^i)] = 0, \tag{6}$$

which states that the incremental benefit from cheating on an existing collusive arrangement ($\pi_i(w_i)$) must equal the expected marginal loss that is incurred if rivals interpret this increase in input prices correctly and adopt a punishment strategy (Green and Porter). Because this condition defines a subgame perfect strategy, every firm in the industry will indeed be expected to follow it and, therefore, never completely defect from the cooperate / punish cartel. In a repeated-game context, however, firms often have both the ability and incentive to renegotiate new equilibrium in order to avoid the punishment phase. Farrell and Maskin are among authors who show that renegotiation reduces the likelihood of observing an effective trigger-price equilibrium, but this ability again depends on the structure of the industry and the nature of rival interactions. Clearly, however, determining whether or not the data are consistent with this conceptual pricing model requires an empirical approach that is able to identify both the exercise of market power during collusive regimes, and the endogenous switch to periods where firms price competitively.

A general model of processor profit maximization under imperfect competition forms the basis for estimating an econometric model of shipper- and retail-level produce price determination. However, given the relationships between buyers and sellers, and among buyers themselves described above the usual approach to modeling Bertrand rivalry must be extended to allow the dynamic Nash behavior described above. Namely, this model must account for the possibility that observed behavior, and the estimated market power parameters, vary both over time and discontinuously by behavioral regime. At the core of the model presented by Green and Porter lies a familiar conduct mechanism similar to that developed by Appelbaum; Bresnahan; or Lau. Our extension to this approach involves estimating endogenous switch points within the sample period that delineate competitive from cooperative periods.

Estimating a model with discontinuous regimes of market power requires the ability to identify two sets of conduct parameters where the switching behavior between the two is determined endogenously. Due to this endogeneity, the switching points between regimes are unidentifiable, or latent quantities. Consequently, this study uses an empirical approach that is able to identify both the degree of market power exercised in each regime and switching points between regimes. To do so, we use a finite mixture estimation (FME) model (Titterington, Smith, and Makov) and estimate it using an expectation / maximization (EM) algorithm (Dempster, Laird, and Rubin). The logic behind this approach is straightforward and well understood in the literature. Further, in order to separate the exercise of market power from the impact of changing supply and demand on produce margins, we develop a model of price determination within each regime of punishment or collusion.

Assume that the produce-retailing industry consists of N firms, all selling a product that is differentiated on the basis of a quality reputation, a market location, or by providing associated retail services to its customers. Further assume that these retailers convert produce at the farm level to saleable goods using the same, fixed proportions technology, herein assumed to be one-for-one without loss of generality. This assumption means that raw inputs are separable from other, non-farm inputs. To simplify notation, assume the production technology can be written as: $x_{ij} = \lambda_{ij} q_{ij}$ where x_{ij} is the amount of produce of type j purchased by retailer i, q_{ij} is the amount of j sold by the ith retailer, and 8_{ij} is a constant of proportionality, assumed here to be 1.

To allow for grower reputations for quality, or simply for the value of relationship-buying among retail agents, the model is cast in a differentiated-product framework where an individual seller's price is allowed to differ from an industry-wide average price. Assuming retailer i receives a price $p_{ij}\ (X_j(W_j, z_2), z_1)$ where $\boldsymbol{z_1}$ is a vector of demand-shifting exogenous variables, $\boldsymbol{z_2}$ is a vector of supply-shifting exogenous variables and W is the industry-wide grower price. Assume each retailer pays its suppliers a price w_{ij} for x_i pounds of produce of type $j\,(X_j = \sum_i x_{ij} \forall j)$ and that the cost of selling produce can be described by a cost function that is separable between buying and selling activities, so that the retailers' profit maximization problem is:

$$\max_{wi}[\pi_i] = \max_{wi}\ [(p_i - w_i)x_i(W) - C(x_i(W), \mathbf{v}]\forall j \in J. \tag{7}$$

Interpreting $x_j(W_j, \boldsymbol{z_2})$ as the supply curve facing each retailer for each commodity, and $p_j(X_j, \boldsymbol{z_1})$ as the inverse retail demand curve - again specific to each seller - and $C(x_i(w_i), \mathbf{v})$ as total cost, a representative retailer's first order condition becomes:

$$\frac{\partial \pi_i}{\partial w_i} = (p_i - w_i)\frac{\partial p_i}{\partial W}\frac{\partial W}{\partial w_i} - x_i(W) + x_i(W)\frac{\partial p_i}{\partial X}\frac{\partial X}{\partial x_i}\frac{\partial x_i}{\partial W}\frac{\partial W}{\partial w_i} - \frac{\partial C}{\partial x_i}\frac{\partial x_i}{\partial W}\frac{\partial W}{\partial w_i} = 0 \tag{8}$$

for each commodity, suppressing the j subscript. Because our data is specific to each retailer, we write firm-level margin equations in terms of supply- and demand-curve slopes and conjectures of both input and output market reactions for each commodity j as:

$$m_i = [p_i - w_i] = c_i + x_i(W)(\eta i \theta i)^{-1} - x_i(W)(\in_i \Phi_i), \tag{9}$$

where c_i is the marginal cost of marketing for firm i, $\mathbf{0}_i$ is the slope of the supply curve facing each firm, 2_i is firm i's conjecture of how the input market price changes for a one unit change in the price it pays, ,i is the slope of each firm's perceived inverse retail demand function, and N_i is the firm-specific conjectural variation in output quantities. Equation (9) is simply a statement of the condition for optimal input employment by a firm with oligopsony and oligopoly power -- that the marginal value product for each input is set equal to its marginal outlay. Whereas the conduct parameter, or conjecture, is typically interpreted as parameterizing the degree of market power, in this application it is more general in that it describes the extent to which conduct is bounded away from perfect competition given that the industry is in a stage of non-cooperative behavior.[3] In order to identify this parameter, however, it is necessary to impose additional restrictions on the slope of the supply curve, 0 and the demand curve, ,.

Typically, this is accomplished by simultaneously estimating input supply and output demand functions wherein their slopes are allowed to vary over time, or to rotate independent of price changes caused by the exercise of market power (Bresnahan). Therefore, input supply is estimated as a function of the grower price, an interaction term between price and another explanatory variable, and a set of other exogenous variables. A similar specification is used for the demand curve. Following Lau or Schroeter and Azzam, the supply curve is specified as a linear function of farm-level own-commodity prices and a set of exogenous factors such as input prices, weather-events, or prices of alternative crops:

$$X(w, z_2) = \alpha_o + \eta^{-1}(w / z_{2k}) + \sum_{i \neq j} \alpha_i z_{2i} + \mu_2, \tag{10}$$

whereas the inverse-demand curve is a function of industry quantity demanded and such demand-shifters as income, alternative commodity prices and seasonal dummy variables:

$$p(X, z_1) = \alpha_o + \in (X / z_{1k}) + \sum_{i \neq k} \alpha_i z_{1i} + \mu_3. \tag{11}$$

With weekly data, this model is estimated assuming fixed weekly effects as supply clearly differs due to seasonal factors. Moreover, we estimate both supply and demand models using two-stage least squares due to assumed endogeneity of grower prices and market demand, respectively. The results obtained by applying these two models to the apple, grape, grapefruit and orange data are found in tables 1 and 2 (apples), tables 4 and 5 (grapes), tables 7 and 8 (oranges) and tables 10 and 11 (grapefruit). For further interpretation of the results shown there, the interested reader is referred to Richards and Patterson (2001). Once the values of 0 and , are substituted into (9), an expression for retail produce marketing costs must be included prior to estimating the entire system.

From the class of flexible functional forms, Diewert's Generalized Leontief (GL) provides several favorable characteristics for the cost function: it is inherently homogeneous in prices without normalization, it is affine in output without further restriction, and it imposes convexity in output, while concavity in prices, symmetry, and monotonicity can be maintained and tested. For a single output (q) and m input prices (vi), the GL cost function becomes:

$$c(x, \mathbf{v}) = x \sum_i \sum_j \gamma_{ij} (v_i v_j)^{1/2} + x^2 \sum_i \gamma_i v_i + \mu_1, \tag{12}$$

---

[3] There is considerable debate on the interpretation of these parameters in the literature. Appelbaum maintains that if 2 = 1 and N = 1, then a retailer behaves as if it is a monopsonist in the input market and a monopolist in the output market, respectively, while if 2 = 0 and N = 0, it behaves as if both the input and output markets are perfectly competitive. However, in a homogeneous product oligopsony with *N* firms it can be shown that 2 is bound by 1/*N* (which implies that 2 goes to zero as *N* becomes large) and 1 if the market price is regarded as an average over all firms' individual prices. On the other hand, N is instead bound by [0, *N*] under these same assumptions. We thank Rich Sexton for these insights.

where :$_1$ is a random error term, and the set of input prices include indices of fuel and electricity prices, business services, and a measure of wages for workers in food retailing. With this specification, derivation of the associated marginal cost function is straightforward. While this model allows the elasticity of supply to vary over time, it is also common to assume that the conduct parameter may also vary with various aspects of the economic environment (Schroeter and Azzam, for example). This is particularly important in our case in order to test the hypothesis that retailer market power falls in the level of fresh produce shipments.

In a more general sense, there may be other factors that influence the exercise of market power. Therefore, define ***K*** as a vector of economic factors that are likely to influence the degree of market power. In particular, if reliable data on concentration levels, barriers to entry or other structural indicators were available on a more frequent basis, then we could directly test the hypothesis that certain structural features may contribute to a retailer's ability to use market power. Limiting the model to the existing data, however, each market power parameter can be written as a linear function of quantity:

$$\begin{aligned}\theta(X|\delta) &= \delta_o + \delta_1(X) + \mu_{4,}\\ \phi(X|\tau) &= \tau_1(x) + \mu_5.\end{aligned} \tag{13}$$

Although it is common practice to estimate equations (9) - (12) simultaneously, this study estimates raw product supply, retail demand and the fresh produce margin equations sequentially due to the added complexity of the multiple-regime finite mixture model.[4] The logic underlying this model and its value in estimating multiple market-power regimes are outlined in the following section.

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[4] Sequential estimation produces parameter estimates that are consistent, but inefficient relative to those found with a full-information estimator such as FIML or 3SLS.

Appendix 2. Finite Mixture Estimation of Switching Regressions Model

Essentially, the FME approach maintains that observations of the dependent variable, retail-shipper margins in the current case, are not drawn from one distribution, but rather two distinct distributions described by unique sets of parameters. In general, Titterington, Smith, and Makov define $f(m_i)$ as a finite mixture distribution of margins over k distinct regimes if:

$$f_i(m_i) = \rho_i f_{1i}(m) + ... + \rho_k f_{ki}(m_i) \qquad (14)$$

where the mixing weights are defined as $\rho_j > 0, \sum_j \rho_j = 1, j = 1,2,\ldots,k$ and the individual densities must, of course, meet the restrictions that: $f_i(> 0, \int f_j(m_i)dm = 1$ Thus, the density for margins is a probabilistically weighted average of each of the component densities (f_j), each with its own mixing weight. Assuming commodity margins are normally distributed, and simplifying the mixture distribution to represent only two regimes, the density can be written as:

$$f_i(m_i | \Omega) = \rho(m_i | \mu_1,\sigma) + (1 - \rho)\psi(m_i | \mu_2,\sigma), \qquad (15)$$

where P is the normal density function, and $\mu_i = Z\alpha_i$ for regime i and a vector of explanatory variables, ***Z***. Wolfe describes a modified likelihood ratio test that is typically used to test the null hypothesis of a two-regime model against a more restrictive single-regime alternative. Wolfe's test is an approximation to likelihood ratio test based on a modified Chi-square distribution with test statistic:

$$S = (2 / N)(n - 1 - d - (C_1 / 2)) \log L, \qquad (16)$$

where L is the value of the likelihood ratio under the null hypothesis of no mixture, N is the sample size, C_1 is the number of components in the mixture (two in our case), and d is the dimension of the underlying normal distribution. The test statistic is Chi-square distributed under the null hypothesis with $2d\ (C_1 - 1)$ degrees of freedom. In terms of the produce buying market structure example, the two regimes are defined by differences in each element of their respective parameter vectors, but most importantly, by differences in the conjectural elasticity of input supply. Modifying equation (9) to be consistent with the switching-regression logic, the margin model becomes:

$$m_{i,t} = \begin{bmatrix} c_{i,t} & withprob.\rho \\ c_{i,t} + (\eta_{i,t}\theta_i)^{-1} x_{i,t} & withprob.(1-\rho \end{bmatrix}, \qquad (17)$$

for each commodity j. However, estimating (15) is not straightforward because the separation points between the two regimes are unobservable.

Unlike Porter (1983), who has data indicating, albeit imperfectly, periods of collusion among nineteenth century railways belonging to the Joint Executive Committee, no such data exists for this study. Therefore, the estimation technique must be able to infer an optimal mixing weight from the data that defines two distinct regimes that are relatively homogeneous within each, but significantly different between.[1] One such latent variable method is the expectation / maximiza-

[1] In this respect, FME is very similar to latent class and cluster analysis.

tion algorithm (EM) (Dempster, Laird, and Rubin). The EM algorithm, also known as the "missing data approach" has become increasingly popular in recent years to estimate a wide variety of latent variable models such as dynamic structural latent variable models or Kalman filters. Dempster, Laird, and Rubin explain the intricacies of this approach, but its fundamental logic is easy to understand.

The estimation method begins in the expectation step, and then iterates between expectation and maximization. Initial estimates of the aggregate mixing weights, or the proportion of observations falling into each regime, are combined with initial model parameters to update the segment weights by calculating the posterior probability of segment membership of each observation. Specifically, these updated weights, s_i, are defined as:

$$
\begin{aligned}
s_{1i} &= \rho(f_{1i} / f_i) \\
s_{2i} &= (1-\rho)(f_{2i} / f_i).
\end{aligned} \tag{18}
$$

Calculating these weights constitutes the expectation step. Next, the updated weights are used to form diagonal matrices $\boldsymbol{S}1$ and $\boldsymbol{S}2$, where:
Each observation is then assigned to a regime depending upon its dominant posterior probability. For example, if observation *i* has a posterior probability of belonging to segment 1 of 0.60 and a probability of belonging to segment 2 of 0.40, then it is assigned to segment 1 and the sample is:

$$
\begin{aligned}
\mathbf{s}_1 &= diag[s_{11}, s_{12}, \ldots, s_{1k} \\
s_2 &= diag[s_{21}, s_{22}, \ldots, s_{2k}.
\end{aligned} \tag{19}
$$

thus delineated for all observations. In the maximization step, new regime-specific response parameters are obtained by weighted least squares:

$$
\begin{aligned}
\alpha_j &= \left[\mathbf{Z}' S_j Z\right]^{-1} Z' S_j m_j \\
\sigma_j^2 &= (1/n_j)(m_j - Z\alpha_j)' S_j (m_j - Z\alpha_j) \\
n_j &= \sum_i^n s_{ij}
\end{aligned} \tag{20}
$$

New aggregate regime shares are found by averaging the weights calculated in (18) over all observations. With these updated aggregate shares, the posterior probability of each observation belonging to each regime is once again found using Bayes' rule (18). These weights are, in turn, used to find new weighted least squares estimates through (20). This process iterates between expectation and maximization until the log-likelihood function changes by less than some prespecified convergence level. Once the model converges, the resulting parameter estimates possess the asymptotic properties of maximum likelihood estimates. These parameters permit tests of a departure from perfectly competitive input pricing if retailers behave according to a very realistic and theoretically consistent model of strategic behavior over time.

Appendix 3. Parameter Estimates

Appendix table 3-1—Washington Red Delicious apples: Supply function 2SLS estimates

Variable	Coefficient	t-ratio
p_g / w_1	7.438*	4.810
W_2	-0.094*	-3.022
W_3	-1.046*	-7.352
W_4	-7.402*	-6.011
P_x	-69.977*	-6.657
p_{po}	-4.338*	-17.340
T	0.184*	16.880
Jan.	-10.269*	-16.090
Feb.	-7.877*	-9.799
Mar.	-7.229*	-9.594
Apr.	-7.111*	-9.670
May	-6.706*	-7.774
June	-8.492*	-9.738
July	-12.098*	-13.760
Aug.	-12.994*	-14.870
Sep.	-12.364*	-15.340
Oct.	-5.680*	-9.405
Nov.	-4.874*	-8.370
Constant	256.170*	15.090
R^2	0.746	
DW	2.287	
BP	8.971	

The variables are defined as follows: p_g = grower price, p_x = export price, p_{po} = processing price (apple juice), w_1 = harvesting labor wage rate, w_2 = price index of agricultural chemicals, w_3 = energy price index, w_4 = interest rate index, t = linear time. A single asterisk indicates significance at a five percent level.

Appendix table 3-2—Market-level Red Delicious retail demand functions: 2SLS estimates

	Market 1		Market 2		Market 3		Market 4		Market 5		Market 6	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
p_r	-0.073*	-1.985	-0.147*	-13.570	-0.951*	-5.621	-0.162*	-8.373	-0.687*	-6.704	-0.358*	-9.932
z_1	0.131	1.433	0.229*	4.127	1.314*	3.968	0.137	1.783	0.850*	2.879	0.430*	2.951
z_2	0.005	0.711	0.001	0.342	0.042	1.532	0.007	1.529	0.023	0.774	-0.007	-0.786
z_3	0.017	0.877	0.031*	4.091	0.062	1.076	-0.013	-1.640	-0.017	-0.323	0.106*	4.785
z_4	-2.086	-0.994	0.222	0.724	-2.242	-0.499	1.038	0.909	12.607	0.974	-5.036*	-2.912
t	0.001	0.862	0.000	-0.942	0.001	0.488	0.000	-1.426	-0.002	-1.167	0.002*	2.726
Chain 2	-0.005	-0.812	0.033*	24.960	-0.035*	-3.237	0.031*	12.300	0.097*	6.444	0.138*	39.82
Chain 3	N.A.	N.A.	0.009*	5.241	-0.035*	-2.179	-0.034*	-12.160	0.054*	3.775	0.003	0.484
Chain 4	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.039*	-8.626	0.102*	7.249	N.A.	N.A.
Chain 5	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.081*	-13.090	N.A.	N.A.	N.A.	N.A.
Constant	0.703	0.993	-0.226	-0.889	1.057	0.457	-0.203	-0.553	-2.324	-0.942	2.009*	2.751
R^2	0.207		0.774		0.387		0.734		0.35		0.872	
DW	2.108		1.363		1.379		1.345		1.619		1.557	
BP	17.433		11.901		6.086		16.396		9.647		20.089	

The variables are defined as follows: p_r = retail price, z_1 = retail price of bananas, z_2 = retail price of table grapes, z_3 = retail price of fresh oranges, z_4 = personal disposable income per capita, t = linear time trend. Note: Jan. - Nov. dummy variable estimates are suppressed for presentation purposes. All Durbin-Watson tests fall in the inconclusive range. Critical chi-square values for the BP test at 5% and 15, 16, 17, and 18 df are 24.996, 26.296, 27.687, and 28.869, respectively. Therefore, we fail to reject the null hypothesis of no heteroscedasticity in each case. A single asterisk indicates significance at a five percent level.

Appendix table 3-3—Summary of apple market power parameter estimates

Chain	$*_0$	$*_1$	Total 2	ϑ_0	ϑ_1	Total N	Weight	Wolfe
Albany: 1	1.008*	-0.007*	0.656*	0.091	-0.001	0.057*	0.653*	
	(22.184)	(-6.585)	(24.295)	(1.429)	(-0.615)	(2.246)	(11.407)	55.607
Albany: 2	1.064*	-0.011*	0.508*	1.813*	-0.011*	1.279*	0.469*	
	(2.901)	(-2.416)	(2.461)	(9.005)	(-3.001)	(10.018)	(5.728)	61.841
Atlanta: 1	0.453*	0.001	0.519*	0.376	0.012	0.973*	0.734*	
	(2.845)	(0.683)	(5.217)	(0.707)	(1.573)	(5.166)	(12.086)	50.243
Atlanta: 2	0.219*	-0.004*	0.033	0.983*	-0.006*	0.676*	0.412*	
	(3.244)	(-4.710)	(0.963)	(25.864)	(-12.097)	(37.484)	(6.004)	80.032
Atlanta: 3	1.943	-0.056*	0.776*	6.609*	-0.084*	1.524*	0.794*	
	(1.903)	(-3.242)	(2.174)	(5.979)	(-4.885)	(7.336)	(14.803)	128.429
Chicago: 1	0.599*	0.002*	0.685*	-0.385*	0.007*	0.033*	0.727*	
	(9.104)	(2.097)	(19.270)	(-23.411)	(23.752)	(5.510)	(13.508)	57.846
Chicago: 2	0.402*	-0.002	0.325*	0.099	-0.001	0.061	0.668*	
	(3.633)	(-1.053)	(5.193)	(1.029)	(-0.521)	(1.032)	(8.469)	65.927
Chicago: 3	1.135*	-0.019*	0.239*	0.035*	-0.001*	0.006*	0.839*	
	(28.278)	(-38.577)	(11.422)	(7.783)	(-12.360)	(4.407)	(22.287)	123.958
Dallas: 1	0.573*	-0.006	0.277*	0.207	0.001	0.210*	0.338*	
	(2.266)	(-1.652)	(2.544)	(1.689)	(0.041)	(5.169)	(5.011)	85.944
Dallas: 2	0.036	0.001	0.059*	0.116*	-0.001*	0.096*	0.754*	
	(1.161)	(1.197)	(4.041)	(19.097)	(-4.709)	(40.822)	(16.063)	66.418
Dallas: 3	-0.156	0.003	0.016	0.831*	-0.001	0.806*	0.624*	
	(-0.798)	(0.944)	(0.213)	(6.139)	(-0.253)	(12.617)	(9.449)	62.43
Dallas: 4	0.432	-0.003	0.243	0.357*	-0.002	0.251*	0.396*	
	1.152	(-0.776)	(1.237)	(2.316)	(-1.082)	(2.714)	(5.001)	48.584
Dallas: 5	0.236	-0.002	0.125	0.611	0.002	0.714	0.641*	
	(0.099)	(-0.069)	(0.094)	(0.521)	(0.119)	(1.528)	(5.996)	53.879
Los Angeles: 1	0.5358*	-0.001	0.468*	-0.014	0.001*	0.052*	0.234*	
	(4.181)	(-0.759)	(6.391)	(-0.337)	(2.019)	(3.918)	(4.120)	111.133
Los Angeles: 2	4.685*	-0.065*	1.562*	0.461*	-0.006*	0.157*	0.809*	
	(8.542)	(-8.323)	(6.718)	(8.373)	(-6.084)	(18.957)	(16.329)	136.696
Los Angeles: 3	0.614*	-0.007*	0.265*	0.145*	-0.002*	0.039*	0.131*	
	(6.807)	(-5.501)	(5.502)	(5.790)	(-5.466)	(5.984)	(21.175)	132.817
Los Angeles: 4	-0.832	0.014	0.764*	0.09	-0.001	0.033*	0.659*	
	(-1.934)	(0.221)	(3.977)	(1.122)	(-0.741)	(2.847)	(10.129)	67.2
Miami: 1	0.215	0.003	0.382	0.256	0.010	0.761*	0.487*	
	(0.348)	(0.394)	(1.243)	(0.424)	(1.313)	(2.458)	(6.394)	58.692
Miami: 2	0.644*	-0.010*	0.162	0.425*	-0.003*	0.269*	0.569*	
	(2.723)	(-2.768)	(1.426)	(9.371)	(-5.328)	(11.085)	(7.256)	37.359
Miami: 3	0.409	0.001	0.427*	0.294*	-0.002	0.171*	0.591*	
	(1.394)	(0.087)	(3.497)	(3.436)	(-1.802)	(3.820)	(8.191)	59.843

The market power parameters are defined by the linear specifications: $\theta = \delta_0 + \delta_1 X$, on the buying side, and $\phi = \tau_0 X$ in the output market for the collusive regime only. For Wolfe's test, the critical chi-square value at 5% and twelve degrees of freedom is 21.026. The values in parentheses are t-rations; a single asterisk indicates significance at a 5% level. In this table, the “weight” parameter is interpreted as the percentage of observations observed in a punishment phase.

Appendix table 3-4—California green seedless grapes: Supply function 2SLS estimates

Variable	Coefficient	t-ratio
$q_{s,\ t-1}$	0.596	1.400
p_g / w_1	-0.672*	-5.169
w_2	-0.227*	-3.178
w_3	-7.433*	-2.783
p_x	-0.006*	-2.518
p_{po1}	-0.005	-1.069
p_{po2}	9.839*	8.834
t	-0.078	-1.495
May	19.563*	3.522
June	19.030*	3.349
July	-11.156*	-2.032
Aug.	19.064*	3.637
Sep.	7.178	1.401
Oct.	2.036	0.412
Nov.	3.969	0.825
Constant	-1351.103*	-8.938
R^2	0.717	
DW-h	0.622	
BP	11.116	

The variables are defined as follows: p_g = grower price, p_x = export price, p_{po1} = processing price (raisins), p_{po2} = processing price (wine), w_1 = harvesting labor wage rate, w_2 = price index of agricultural chemicals, w_3 = energy price index, w_4 = interest rate index, t = linear time trend. A single asterisk indicates significance at a 5% level. The critical value of the BP test with 16 degrees of freedom at a 5% level is 26.696. The DW-h statistic is asymptotically normal.

Appendix table 3-5—Market-level green seedless grape retail demand functions: 2SLS estimates

	Market 1		Market 2		Market 3		Market 4		Market 5		Market 6	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
$p_r z_1$	-0.163*	-9.885	-0.011*	-4.196	-0.131*	-3.732	-0.083*	-8.673	-0.211*	-8.592	-0.031*	-3.062
z_2	0.551*	2.333	-0.026	-0.808	-1.549*	-3.36	-0.025	-0.204	0.779	1.935	-0.163	-1.343
z_3	0.024	0.383	-0.007	-1.39	0.256	1.554	-0.039	-1.387	-0.494*	-4.798	-0.123*	-5.675
z_4	-9.644*	-2.229	-0.522*	-3.745	-20.871*	-4.276	-6.332*	-4.092	-61.329*	-5.224	-2.046	-1.622
t	0.004*	2.293	0.003*	3.771	0.011*	4.016	0.002*	4.676	0.009*	5.043	0.009*	2.017
Chain 2	0.005	0.259	0.037*	29.31	-0.141*	-4.491	-0.072*	-9.743	0.097*	4.031	0.034*	7.196
Chain 3	N.A.	N.A.	-0.005*	-3.199	0.085*	2.005	-0.089*	-10.501	0.015	0.609	-0.008*	-9.249
Chain 4	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.091*	-5.701	0.182*	6.984	N.A.	N.A.
Chain 5	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.136*	-5.981	N.A.	N.A.	N.A.	N.A.
Constant	3.145*	2.14	0.455*	3.868	11.334*	4.569	2.19*	4.467	11.979*	5.257	1.116*	2.12
R^2	0.456		0.871		0.462		0.499		0.433		0.598	
DW	1.873		1.904		1.963		1.704		2.354		1.773	
BP	7.773		2.835		4.699		2.951		5.911		2.891	

The variables are defined as follows: p_r = retail price, z_1 = retail price of bananas, z_2 = retail price of apples, z_3 = retail price of fresh oranges, z_4 = personal disposable income per capita, t = linear time trend.
Note: June - Dec. dummy variable estimates are suppressed for presentation purposes. All Durbin-Watson tests fall in the inconclusive range. Critical chi-square values for the BP test at 5% and 15, 16, 17, and 18 df are 24.996, 26.296, 27.687, and 28.869, respectively. Therefore, we fail to reject the null hypothesis of no heteroscedasticity in each case.

Appendix table 3-6—California green seedless grapes: Market power estimate summary

Chain	$*_0$	$*_1$	Total 2	ϑ_0	ϑ_1	Total N	Weight	Wolfe
Albany: 1	-0.005*	1.476*	0.003*	1.573*	0.002	1.574*	0.787*	
	(-4.280)	(-5.308)	(3.227)	(3.872)	(0.011)	(4.402)	(12.862)	106.036
Albany: 2	0.001	-0.032	-0.001	2.435*	-7.764*	1.987*	0.686*	
	(0.504)	(-1.158)	(-0.255)	(10.829)	(-9.020)	(8.765)	(9.737)	86.561
Atlanta: 1	-0.003*	6.929*	0.001	1.229*	-2.481*	1.091*	0.800	
	(-3.448)	(2.033)	(0.015)	(6.365)	(-3.054)	(6.018)	(15.901)	143.975
Atlanta: 2	-4.165*	9.126*	-0.277*	-3.532*	8.395*	0.441	0.582*	
	(-11.995)	(12.503)	(-3.680)	(-8.168)	(12.114)	(1.929)	(8.764)	74.656
Atlanta: 3	0.059	4.999	0.076*	0.03	3.906	0.155	0.513*	
	(1.889)	(0.702)	(3.368)	(0.049)	(0.739)	(0.304)	(5.944)	47.359
Chicago: 1	0.002	-0.113	0.002	-0.048	0.248*	0.471*	0.465*	
	(1.896)	(-0.806)	(1.953)	(-4.515)	(4.454)	(4.448)	(7.238)	178.797
Chicago: 2	-0.033*	0.001*	0.007	-1.386*	0.021*	-0.356*	0.324*	
	(-2.587)	(3.134)	(1.366)	(-3.088)	(2.177)	(-3.045)	(3.887)	104.317
Chicago: 3	-0.092*	0.002*	-0.015*	-0.014	0.001	0.020*	0.525	
	(-6.859)	(6.899)	(-3.310)	(-0.455)	(1.250)	(2.109)	(0.084)	38.547
Dallas: 1	0.222*	-0.004*	0.027*	0.463*	-0.007*	0.127*	0.664*	
	(23.520)	(-31.409)	(4.946)	(7.503)	(-7.623)	(6.822)	(10.066)	46.931
Dallas: 2	-0.010	0.001	0.019*	-0.787*	0.009	-0.321	0.775*	
	(-0.760)	(1.873)	(2.661)	(-2.517)	(1.781)	(-3.687)	(11.083)	93.375
Dallas: 3	-0.149*	0.001	-0.097*	0.612	-0.009	0.193*	0.675*	
	(-3.547)	(1.659)	(-5.339)	(-0.009)	(-1.728)	(2.025)	(8.994)	45.523
Dallas: 4	-0.082*	0.001*	0.058*	-1.019*	0.016*	0.055	0.403*	
	(-2.760)	(3.165)	(4.172)	(-2.600)	(2.716)	(0.437)	(5.222)	81.278
Dallas: 5	0.589	-0.001	0.017	1.026	-0.003	0.866*	0.748*	
	(1.116)	(-0.944)	(1.272)	(1.496)	(-0.248)	(2.948)	(10.688)	72.512
Los Angeles: 1	0.118	-0.003*	-0.023	1.964*	-0.021*	0.911*	0.733*	
	(1.557)	(-2.331)	(-0.897)	(3.662)	(-2.721)	(4.324)	(10.253)	63.011
Los Angeles: 2	-0.028	-0.001	0.028	0.017	0.001	0.019	0.608*	
	(-0.525)	(-0.362)	(0.341)	(0.127)	(0.157)	(0.289)	(6.727)	49.381
Los Angeles: 3	-0.089	0.001	-0.018	0.116*	0.019	1.094*	0.613*	
	(-0.969)	(0.965)	(-0.719)	(2.561)	(1.107)	(2.947)	(8.801)	139.519
Los Angeles: 4	0.273*	-0.003	0.121*	0.432*	-0.007	0.084	0.600*	
	(2.775)	(-1.881)	(3.649)	(1.967)	(-1.523)	(1.451)	(6.397)	51.094
Miami: 1	0.661*	-0.006*	0.292*	0.789*	-0.008	0.393*	0.650*	
	(3.027)	(-2.743)	(3.104)	(2.786)	(-1.717)	(5.184)	(8.423)	84.335
Miami: 2	0.092*	-0.001*	0.042*	0.213*	-0.001*	0.145*	0.780*	
	(20.951)	(-14.027)	(18.331)	(25.167)	(-8.877)	(48.187)	(13.763)	126.31
Miami: 3	0.005	0.002*	0.080*	-2.724*	0.337*	0.416*	0.552*	
	(0.134)	(2.787)	(4.334)	(-5.925)	(6.124)	(3.952)	(5.893)	55.34

The market power parameters are defined by the linear specifications: $\theta = \delta_0 + \delta_1 X$, on the buying side, and $\phi = \tau_0 X$ in the output market for the collusive regime only. The critical chi-square value at 5% and twelve degrees of freedom is 21.026. For all other variables, a single asterisk indicates significance at a 5% level. In this table, the "weight" parameter is interpreted as the probability an observation is in a punishment phase.

Appendix table 3-7—California fresh oranges: Supply function 2SLS estimates

Variable	Coefficient	t-ratio
$q_{s,\,t-1}$	0.278*	20.14
$p_g\, w_1$	5.461*	19.450
w_2	-1.698*	-7.472
w_3	-17.694*	-5.489
p_x	-0.785*	-8.957
Mar.	-171.54	-13.550
Apr.	-322.660*	-19.530
May	-361.510*	-23.350
June	-531.130*	-36.210
July	-196.740*	-12.380
Aug.	-303.720*	-21.870
Sep.	-582.540*	-33.980
Oct.	-472.440*	-28.310
Nov.	-306.000*	-18.03
Constant	3322.800*	8.126
R^2	0.792	
DW-h	1.456	
BP	3.745	

The variables are defined as follows: p_g = grower price, p_x = export price, w_1 = harvesting labor wage rate, w_2 = price index of agricultural chemicals, w_3 = energy price index. A single asterisk indicates significance at a 5% level. The critical value of the BP test with 15 degrees of freedom is 24.996. The DW-h statistic is asymptotically normal.

Appendix table 3-8—Market-level fresh orange retail demand functions: 2SLS estimates

	Market 1		Market 2		Market 3		Market 4		Market 5		Market 6	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
p_r/z_1	-330.56*	-7.54	-6.979	-1.293	-347.450*	-3.739	-53.606*	-3.708	-413.460*	-6.861	-91.942*	-4.099
z_2	677.140*	3.262	167.020*	2.225	-655.960	-1.015	286.290*	2.768	-988.280*	-2.387	432.280*	2.060
z_3	7.337	0.146	11.712	1.640	494.620*	3.172	52.179*	4.270	-151.380*	-2.034	36.382	1.504
z_4	3.281	0.619	1.052*	3.782	7.251	0.856	2.547*	2.185	1.529	1.116	7.006*	3.604
t	-1.299	-0.670	-0.692*	-3.878	-4.431	-0.999	-0.928*	-2.995	-4.426*	-1.970	-3.135*	-4.422
Chain 2	66.350*	3.440	66.457*	33.110	-267.790*	-6.803	-34.042*	-7.362	123.480*	6.495	82.068*	11.010
Chain 3	N.A.	N.A.	6.229*	2.598	61.424	1.493	-66.220*	-14.600	68.638*	3.762	-39.689*	-3.425
Chain 4	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-17.656*	-2.561	90.817*	4.567	N.A.	N.A.
Chain 5	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-42.025*	-3.952	N.A.	N.A.	N.A.	N.A.
Constant	-1.255	-0.698	-0.917*	-4.170	-3.463	-0.791	-0.835*	-2.344	-1.545	-0.603	-3.000*	-3.801
K	15		16		16		18		17		16	
R^2	0.647		0.872		0.429		0.711		0.589		0.779	
DW	1.435		1.638		1.489		1.809		1.841		1.705	
BP	2.592		4.738		4.826		7.805		6.112		9.213	

The variables are defined as follows: p_r = retail price, z_1 = retail price of bananas, z_2 = retail price of apples, z_3 = retail price of table grapes, z_4 = personal disposable income per capita, t = linear time trend. Note: Mar. - Nov. dummy variable estimates are suppressed for presentation purposes. All Durbin-Watson tests fall in the inconclusive range. Critical chi-square values for the BP test at 5% and 15, 16, 17, and 18 df are 24.996, 26.296, 27.687, and 28.869, respectively. Therefore, we fail to reject the null hypothesis of no heteroscedasticity in each case.

Appendix table 3-9—Summary of orange market power parameter estimate

Chain	*0	*1	Total 2	ϑ_0	ϑ_1	Total N	Weight	Wolfe
Albany: 1	0.499*	-0.003*	0.308*	-0.168*	0.002*	0.057*	0.588*	
	(2.892)	(2.722)	(2.658)	(-2.950)	(2.226)	(3.219)	(8.252)	71.577
Albany: 2	0.618*	-0.002	0.428*	0.221	0.001	0.255*	0.755*	
	(2.191)	(-1.195)	(2.159)	(1.507)	(0.241)	(6.802)	(14.357)	84.525
Atlanta: 1	1.770*	-0.001*	0.994*	-1.535	0.005	1.832*	0.632*	
	(2.608)	(-3.564)	(2.086)	(-0.699)	(1.856)	(3.101)	(9.162)	95.816
Atlanta: 2	-0.572	0.001*	0.119	-0.132	0.004	0.118*	0.666*	
	(-1.086)	(2.703)	(0.310)	(-0.755)	(1.282)	(2.713)	(8.449)	66.293
Atlanta: 3	-0.112	0.001	-0.043	0.241	0.001	0.299*	0.801*	
	(-0.851)	(1.369)	(-0.479)	(0.750)	(0.195)	(2.321)	(16.504)	188.045
Chicago: 1	0.618	-0.001	0.508	0.099	-0.001	0.027	0.469*	
	(0.933)	(-0.312)	(1.446)	(0.964)	(-0.669)	(0.972)	(7.548)	145.224
Chicago: 2	0.122	-0.001*	0.038	0.065	-0.006	0.023	0.572*	
	(1.609)	(-3.161)	(0.698)	(0.513)	(-0.376)	(0.805)	(7.492)	52.299
Chicago: 3	1.759*	-0.001*	0.813*	-0.025	0.001*	0.045*	0.619*	
	(9.098)	(-10.421)	(7.182)	(-1.137)	(3.542)	(8.482)	(8.197)	53.485
Dallas: 1	0.755*	-0.001*	0.372*	0.136*	0.001	0.183*	0.572*	
	(3.479)	(-5.005)	(2.313)	(2.571)	(0.784)	(7.083)	(9.183)	79.301
Dallas: 2	0.243	-0.001	0.161	0.123	-0.003*	-0.068*	0.611*	
	(1.638)	(-1.197)	(1.686)	(1.681)	(-2.494)	(-1.972)	(9.616)	78.429
Dallas: 3	0.192*	-0.002	0.177*	0.267*	-0.001	0.143*	0.727*	
	(1.638)	(-1.197)	(1.686)	(1.681)	(-2.494)	(-1.972)	(9.616)	82.927
Dallas: 4	-1.210*	0.001*	-0.5818	-0.479*	0.001*	0.111*	0.564*	
	(-5.814)	(6.196)	(-4.154)	(-3.297)	(4.521)	(3.527)	(8.817)	74.411
Dallas: 5	-0.387*	0.002*	-0.242*	-0.073	-0.001	-0.117*	0.495*	
	(-3.336)	(2.239)	(-3.701)	(-0.476)	(-0.322)	(-2.201)	(6.260)	55.976
Los Angeles: 1	-0.267	0.002	0.021	0.176*	0.001	0.045*	0.625*	
	(-0.735)	(1.021)	(0.132)	(2.489)	(0.723)	(2.513)	(9.787)	86.806
Los Angeles: 2	-0.164	0.001*	0.068	0.036*	-0.001	0.027*	0.650*	
	(-1.501)	(2.885)	(0.823)	(3.043)	(-0.733)	(15.686)	(12.144)	128.209
Los Angeles: 3	-0.233	0.004*	0.030	-0.022	0.005	0.012*	0.525*	
	(-1.560)	(4.351)	(0.303)	(-1.145)	(1.840)	(3.553)	(8.713)	118.739
Los Angeles: 4	2.627*	-0.002*	1.164*	0.233*	-0.018	0.120*	0.593*	
	(4.832)	(-5.570)	(3.530)	(2.883)	(-1.476)	(3.076)	(8.740)	69.683
Miami: 1	0.371	-0.002*	0.495*	1.296*	-0.007*	0.862*	0.686*	
	(1.677)	(-2.105)	(2.896)	(8.933)	(-3.447)	(17.761)	(10.749)	49.831
Miami: 2	0.249	-0.001*	0.130	0.014	0.001	0.024	0.614*	
	(1.951)	(-3.154)	(1.393)	(0.513)	(0.478)	(1.802)	(7.804)	48.282
Miami: 3	0.537*	-0.002*	0.384*	0.129	0.003	0.147	0.387*	
	(3.278)	(-2.530)	(3.535)	(0.604)	(0.109)	(1.509)	(5.551)	101.594

The market power parameters are defined by the linear specifications: $\theta = \delta_0 + \delta_1 X$, on the buying side, and $\phi = \tau_0 X$ in the output market for the collusive regime only. The critical chi-square value at 5% and twelve degrees of freedom is 21.026. For all other variables, a single asterisk indicates significance at a 5% level. In this table, the "weight" parameter is interpreted as the probability of an observation being in a punishment phase.

Appendix table 3-10—Fresh grapefruit: Supply function 2SLS estimates

Variable	Coefficient	t-ratio
$p_g\ / w_1$	7.259*	4.52
w_2	-209.610*	-13.92
w^3	-71.895*	-11.45
w_4	40.136*	4.869
p_x	-1.800*	-13.67
p_{po}	-14.856*	-5.826
t	0.002*	2.064
Jan.	-71.172*	-4.853
Feb.	-120.520*	-7.774
Mar.	3.085	0.2332
Apr.	-161.400*	-12.41
May	-401.240*	-34.63
Sep.	-506.300*	-28.22
Oct.	-183.830*	-14.52
Nov.	-174.390*	-17.21
Constant	11.612*	13.62
R^2	0.888	
DW	1.479	
BP	0.721	

The variables are defined as follows: p_g = grower price, p_x = export price, w_1 = harvesting labor wage rate, w_2 = price index of agricultural chemicals, w_3 = energy price index. A single asterisk indicates significance at a 5% level. The critical value of the BP test with 18 degrees of freedom is 28.869.

Appendix table 3-11—Market-level fresh grapefruit retail demand functions: 2SLS estimates

	Market 1		Market 2		Market 3		Market 4		Market 5		Market 6	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
$p_r z_1$	-0.073*	-1.985	-0.147*	-13.570	-0.951*	-5.621	-0.162*	-8.373	-0.687*	-6.704	-0.358*	-9.932
z_1	0.131	1.433	0.229*	4.127	1.314*	3.968	0.137	1.783	0.850*	2.879	0.430*	2.951
z_2	0.005	0.711	0.001	0.342	0.042	1.532	0.007	1.529	0.023	0.774	-0.007	-0.786
z_3	0.017	0.877	0.031*	4.091	0.062	1.076	-0.013	-1.64	-0.017	-0.323	0.106*	4.785
z_4	-2.086	-0.994	0.222	0.724	-2.242	-0.499	1.038	0.909	12.607	0.974	-5.036*	-2.912
t	0.001	0.862	0.000	-0.942	0.001	0.488	0.000	-1.426	-0.002	-1.167	0.002*	2.726
Chain 2	-0.005	-0.812	0.033*	24.960	-0.035*	-3.237	0.031*	12.300	0.097*	6.444	0.138*	39.82
Chain 3	N.A.	N.A.	0.009*	5.241	-0.035*	-2.179	-0.034*	-12.160	0.054*	3.775	0.003	0.484
Chain 4	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.039*	-8.626	0.102*	7.249	N.A.	N.A.
Chain 5	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.081*	-13.090	N.A.	N.A.	N.A.	N.A.
Constant	0.703	0.993	-0.226	-0.889	1.057	0.457	-0.203	-0.553	-2.324	-0.942	2.009*	2.751
K	15		16		16		18		17		16	
R^2	0.637		0.812		0.696		0.755		0.424		0.943	
DW	1.883		2.152		2.112		1.276		1.377		1.988	
BP	2.24		4.652		3.073		5.544		6.172		16.022	

The variables are defined as follows: p_r = retail price, z_1 = retail price of bananas, z_2 = retail price of apples, z_3 = retail price of table grapes, z_4 = personal disposable income per capita, t = linear time trend.
Note: Mar. - Nov. dummy variable estimates are suppressed for presentation purposes. All Durbin-Watson tests fall in the inconclusive range. Critical chi-square values for the BP test at 5% and 15, 16, 17, and 18 df are 24.996, 26.296, 27.687, and 28.869, respectively. Therefore, we fail to reject the null hypothesis of no heteroscedasticity in each case.

Appendix table 3-12—Summary of grapefruit market power parameter estimate

Chain	*$_0$	*$_1$	Total 2	ϑ_0	ϑ_1	Total N	Weight	Wolfe
Albany: 1	-0.516	-0.004	-0.244	0.462*	-0.005*	0.1808*	0.601*	
	(-0.194)	(-1.405)	(-1.155)	(4.497)	(-2.696)	(10.667)	(6.709)	43.429
Albany: 2	-0.437	-0.012*	-1.085*	2.632*	-0.003*	1.011*	0.371*	
	(-0.812)	(-4.094)	(-2.583)	(9.003)	(-6.115)	(23.011)	(5.561)	45.453
Atlanta: 1	0.475*	-0.003*	0.318*	0.662*	0.002*	1.675*	0.206*	
	(34.218)	(-25.697)	(36.781)	(10.503)	(20.757)	(113.800)	(3.986)	78.636
Atlanta: 2	2.073*	-0.005*	1.811*	-0.074*	0.001*	0.413*	0.208*	
	(58.582)	(-11.754)	(34.895)	(-2.159)	(14.578)	(386.911)	(4.039)	97.563
Atlanta: 3	15.473*	-0.029*	0.03	0.779*	-0.008*	0.350*	0.219*	
	(14.414)	(-28.686)	(0.046)	(73.345)	(-40.526)	(180.077)	(4.137)	86.616
Chicago: 1	2.969*	-0.025*	1.644*	-0.039	0.001	0.0568*	0.376*	
	(5.584)	(-4.654)	(4.376)	(-0.347)	(0.866)	(2.255)	(5.335)	43.546
Chicago: 2	1.611*	-0.011*	0.981*	-0.406*	0.001*	-0.065*	0.261*	
	(28.936)	(-8.472)	(12.356)	(-2.596)	(2.624)	(-2.263)	(4.563)	95.931
Chicago: 3	1.920*	-0.028*	0.435*	0.427*	-0.001*	0.055*	0.276*	
	(43.275)	(-74.792)	(16.045)	(100.828)	(-99.085)	(35.526)	(4.781)	73.533
Dallas: 1	0.984*	0.001	1.056*	-0.564*	0.002*	0.532*	0.266*	
	(4.565)	(0.509)	(6.905)	(-3.278)	(5.774)	(7.329)	(4.511)	52.767
Dallas: 2	0.249*	0.004	0.272*	0.206*	0.004*	0.454*	0.214*	
	(2.575)	(0.410)	(6.749)	(20.020)	(18.392)	(80.829)	(4.185)	114.884
Dallas: 3	0.161	0.014*	0.934*	-2.984*	0.006*	0.550*	0.214*	
	(1.041)	(6.279)	(19.493)	(-18.919)	(17.895)	(13.530)	(4.192)	116.826
Dallas: 4	0.008*	-0.001*	-0.047*	0.042*	-0.001*	0.003*	0.213*	
	(3.311)	(-74.880)	(-25.733)	(82.154)	(-99.189)	(18.952)	(4.181)	117.36
Dallas: 5	-0.186*	0.008*	-0.143*	2.125*	-0.001*	1.596*	0.329*	
	(-10.011)	(6.587)	(-11.516)	(28.259)	(-7.401)	(132.702)	(5.121)	89.842
Los Angeles: 1	-0.181	0.007	0.194	-0.269	0.001	0.549*	0.215*	
	(-0.266)	(0.949)	(0.486)	(-0.527)	(1.924)	(2.947)	(4.203)	151.681
Los Angeles: 21	0.072	0.003	0.089	0.091	-0.001	0.026	0.203*	
	(0.104)	(0.056)	(0.182)	(0.845)	(-0.616)	(1.821)	(3.918)	62.949
Los Angeles: 3	0.563*	-0.008*	0.137*	0.302*	-0.003*	0.133*	0.243*	
	(120.957)	(-251.958)	(41.229)	(272.496)	(-181.513)	(697.101)	(4.536)	131.107
Los Angeles: 4	2.078*	-0.021*	0.919*	0.152*	-0.001*	0.093*	0.263*	
	(18.277)	(-19.419)	(15.005)	(33.404)	(-12.851)	(79.614)	(4.654)	75.827
Miami: 1	3.643*	-0.034*	1.722*	0.119*	-0.001*	0.091*	0.226*	
	(135.500)	(-122.942)	(136.781)	(100.459)	(-23.048)	(185.329)	(4.302)	103.327
Miami: 2	-1.087*	0.009*	-0.572*	0.254*	-0.002*	0.089*	0.212*	
	(-98.347)	(76.822)	(-114.884)	(265.745)	(-239.673)	(251.729)	(4.129)	101.726
Miami: 3	1.429*	-0.010*	0.842*	0.149*	-0.001*	0.096*	0.224*	
	(7.656)	(-6.091)	(8.935)	(18.841)	(-6.395)	(42.319)	(4.054)	59.679

The market power parameters are defined by the linear specifications: $\theta = \delta_0 + \delta_1 X$, on the buying side, and $\phi = \tau_0 X$ in the output market for the collusive regime only. The critical chi-square value at 5% and twelve degrees of freedom is 21.026. For all other variables, a single asterisk indicates significance at a 5% level. In this table, the "weight" parameter is interpreted as giving the probability of an observation being in a punishment phase.