Price Flexibility in Channels of Distribution: Evidence from Scanner Data*

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Abstract

In this study, we empirically examine the extent of price rigidity using a unique store-level time series data set—consisting of (i) actual retail transaction prices, (ii) actual wholesale transaction prices which represent both the retailers’ costs and the prices received by manufacturers, and (iii) a measure of manufacturers’ costs—for twelve goods in two widely used consumer product categories. We simultaneously examine the extent of price rigidity for each of the twelve products we study at both, final goods and intermediate goods levels. We study two notions of price rigidity employed in the existing literature: (i) the frequency of price changes, and (ii) the response of prices to exogenous cost changes. We find that retail prices exhibit remarkable flexibility in terms of both notions of price rigidity. i.e., they change frequently and they seem to respond quickly and fully to cost changes. Furthermore, we find that retail prices respond not just to their direct costs, but also to the upstream manufacturers’ costs, which further reinforces the extent of the retail price flexibility. At the intermediate goods level of the market, in contrast, we find relatively more evidence of rigidity in the response of manufacturers prices to cost changes. This despite the fact that wholesale prices change frequently and therefore exhibit flexibility according to the first notion of price rigidity.
1. Introduction

Price rigidity, the apparent sluggish and incomplete response of prices to nominal shocks, is important enough to occupy a central stage in the research program of new Keynesian macroeconomics (e.g., Rotemberg, 1987; Mankiw and Romer, 1991; Ball and Mankiw, 1995; Blinder, 1994) and industrial organization (e.g., Stigler and Kindahl, 1970; Stiglitz, 1984; and Carlton, 1989). Despite its central importance, the empirical evidence on the rigidity of prices is limited. As emphasized by authors such as Carlton (1986), Gordon (1990), and Kashyap (1995), there are only a handful of time series studies of price flexibility that use actual transaction prices. In this study, we empirically examine the extent of price rigidity using a unique store level time series data set—consisting of (i) actual retail transaction prices, (ii) actual wholesale transaction prices which represent both the retailers’ marginal cost, and the prices received by manufacturers, and (iii) a measure of manufacturers’ costs—for twelve goods in two widely used consumer product categories. The data set has several distinguishing features which make it particularly suitable for studying price rigidity. In particular, the cost data are exogenous with respect to prices and exhibit significant variation over the sample period. In addition, the products we study have constant quality.

We contribute to the literature on price rigidity in a number of ways. First, this data set allows us to examine two notions of price rigidity employed in the existing literature. We first examine price rigidity indirectly by studying the frequency of price changes, the distribution of the time interval between price changes, etc. However, as Blinder (1991, pp. 93–94) suggests, “From the point of view of macroeconomic theory, frequency of price changes may not be the right question to ask ... We are more interested to know how long price adjustments lag behind shocks to demand and cost.” In fact, according to Carlton and Perloff’s (1994) definition, “Price rigidity is said to occur when prices do not vary in response to fluctuations in costs and demand” (p. 722). The availability of cost data enables us to examine this direct notion of price rigidity, extending the work of Cecchetti (1986), Hannan and Berger (1991), Neumark and Sharpe (1993), and Kashyap (1995).

Second, our data allow us to study the degree of retail price rigidity. Lach and Tsiddon (1992, 1996) and Warner and Barsky (1995), among others, suggest that store-level individual price data is most appropriate for studying nominal price rigidity, since the retailer actually sets final goods prices. Further, our two product categories are made up of small representative staple retail items which are often suggested as an appropriate product category for studying price rigidity (Hannan and Berger, 1991; Neumark and Sharpe, 1993; and Ball and Mankiw, 1995). Third, the data also enable us to examine the rigidity of intermediate goods prices.

Fourth, our data set allows us to study the extent of price rigidity at both retail (final good) and manufacturing (intermediate good) levels of the channel for the same twelve products we study,

simultaneously. Most of the existing studies of price rigidity only study one level at a time, either the rigidity of intermediate goods prices or the rigidity of final goods prices. However, Gordon (1990) suggests the importance of simultaneously considering multiple levels of a market for studying price rigidity because of the interdependence of price and cost setting decisions across channels. We study the interaction between the manufacturing and retail levels by analyzing how upstream manufacturer cost changes (in addition to the direct costs) affect retail pricing decisions. The cross-channel comparison we make here is unique since the products compared across the two channels are identical.

And fifth, we use these data to empirically explore the relationship between stages of processing and price rigidity. Several authors such as Blanchard (1983), Mankiw (1985), Gordon (1990), Blinder (1994), and Basu (1995), suggest that the existence of stages of processing may be contributing to sluggish adjustment of final prices to upstream cost changes in many markets. For example, according to Blanchard’s (1983) model, price rigidity will positively depend on the number of stages of processing. In this context, Gordon (1990) argues that prices will be more flexible in the case of “simple” products, that is, products produced using a small number of inputs.

To briefly summarize our findings, at the retail level we find that retail prices are flexible in terms of both notions of price rigidity: (i) they change frequently, and (ii) they respond quickly and fully to changes in costs. This finding suggests that retail prices of some consumer goods may be more flexible than documented in the existing literature. At the intermediate level we find evidence of the second notion of price rigidity, i.e., rigidity in the response of manufacturers prices to their cost changes. We find this rigidity even though wholesale prices change frequently and therefore exhibit flexibility according to the first notion of price rigidity.

But perhaps the most striking finding we report in this paper is that the retail prices seem to respond not just to their direct costs, but also to the upstream manufacturers’ costs. This reinforces the finding of retail price flexibility, and suggests that it is important to view prices in the context of all costs, both direct and indirect. Although this raises the possibility that in certain settings the existence of stages of processing may not be a barrier to cost shocks’ downstream passthrough, it should be noted that our findings may still be consistent with the predictions of the models of stages of processing. This is because in the market we study, the production channel consists of only two stages of processing. This allows cost change information quickly flow downstream which leading to a fast passthrough of cost changes onto prices. Also considering the orange juice market structure and given that the products we study are “simple” in the sense that the number of inputs used in their production is small, perhaps it should not be surprising that we find this retail price flexibility.

The paper is organized as follows. We begin with a section describing the data set used in this study. The following section describes the econometric model. Next we discuss our results for the retail
level of the channel followed by the discussion of the results for the wholesale level of the channel. We end
with conclusions and future extensions.

2. Data

The data set used in this study consists of 88 weekly observations, covering the period from October
5, 1989 to June 6, 1991. It consists of spot prices of frozen concentrated orange juice, and the wholesale
and retail prices of three brands of orange juice (two national brands, Tropicana and Minute Maid, and one
private label, Heritage House) in two product categories (frozen concentrated and refrigerated made from
frozen concentrate). Each brand of frozen concentrated orange juice comes in two sizes, 12oz (which is
considered the standard size) and 16oz. Similarly, each brand of refrigerated orange juice made from
concentrate comes in two sizes, 64oz (which is considered the standard size) and 96oz (128oz for Heritage
House). Thus, we study a total of 12 products. The spot prices are constructed from the futures price of
frozen concentrated orange juice as reported by the New York Cotton Exchange (NYCE). The wholesale
and retail prices come from a scanner data set of Dominick’s, a large Midwestern supermarket chain
operating over 80 stores throughout Midwest. The pricing, inventory management, purchasing, and
promotion practices at Dominick’s are representative of many large U.S. grocery chains.

To better understand the data we use, we present in Chart 1 a general schematic description of the
organizational structure of the frozen concentrated orange juice market. Orange juice growers sell the fruit to
orange juice processors who convert the oranges into frozen concentrate. There are two types of processors:
one group of processors are privately owned and produce orange juice for private label. The other group of
processors are owned by national orange juice manufacturers like Tropicana and Minute Maid, and they
produce nationally branded products. These manufacturers package and sell the concentrated juice to
retailers, either in its frozen form or reconstituted from concentrate and packaged as refrigerated juice.

In this paper we study two levels of the distribution channel: the retail level which represents the final
goods level of the market, and the manufacturer level which represents the intermediate goods level of the
market. As Chart 1 suggests, the market we study has a hierarchical structure similar to the stages-of-
processing structure of Blanchard (1983). This is different from the input-output structure emphasized by
Gordon (1990), Meltzer (1994), and Basu (1995). As Gordon (1990) suggests, the input-output view of
the market organization is better suitable for more aggregated (e.g., industry level), and more complex
products produced using many inputs. Here, by contrast, we study individual products, and also the
products themselves are simple, produced with only few inputs.

The data set has several unique features which make it particularly suitable for studying price rigidity:

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2 Private label refers to the in-house or store brand which is usually owned by a particular retail chain.

3 In this paper the cost-price relationship at the manufacturing (intermediate goods) stage is sometimes described as spot-to-wholesale, and the cost-price relationship at the retail (final goods) stage is described as wholesale-to-retail. Similarly, in the case of the effect of upstream costs on retail price, we use the term spot-to-retail.
(1) Actual retail prices: For the final price to consumers at the retail level, we use weekly scanner data from a large Midwestern supermarket chain, Dominick’s. These are the actual prices consumers paid at the cash register each week. If the item was on sale, then the price data we have reflects the sale price.\(^4\) The retail prices are set on a chain-wide basis at the corporate headquarters of Dominick’s, which is a standard practice for supermarket chains (Chevalier, 1995), and the data we have comes from a representative store of this chain. The advantage of using actual store-level price data over aggregate price indices (such as those constructed by the Bureau of Labor Statistics) for studying price rigidity is that individual product price data collected at the store level most closely resemble the data envisioned by nominal price adjustment theories, since this is where prices are actually set (Lach and Tsiddon, 1992 and 1996; Warner and Barsky, 1995; and Wynne, 1995). Further, by using the actual price data, we avoid potential biases associated with the use of more aggregated data (Carlton, 1989).

(2) Wholesale Prices: Actual retail cost and actual manufacturers’ prices: As a measure of the direct cost to the retailer, we use the actual price the retailer paid the orange juice manufacturer, i.e., the wholesale price. The wholesale price was computed from the information provided by the retailer on their retail prices and weekly margins for each product.\(^5\) Having access to this cost data allows us to use a direct measure of cost rather than an indirect or aggregate measure such as GNP deflator, CPI, etc. Several authors, such as Gordon (1990) and Basu (1995), suggest the importance of using direct cost data for studying pricing decisions. The availability of direct cost data enables us to study the second notion of price rigidity, specifically how prices respond to direct cost changes. Further, access to retail costs is rare. Even in studies that use scanner data, retailer costs are usually proprietary and seldom reported.

The wholesale price is the actual price the manufacturers receive from the retailer, and enables us to study patterns of price rigidity at the manufacturing stage of the channel. Again, this actual transaction price is particularly appropriate for studying price rigidity and eliminates possible biases associated with the use of

\(^4\) Our retail prices reflect any retailer’s coupons or discounts, but do not include manufacturer coupons. Fortunately, during the period covered in this study manufacturer coupons were rarely used to promote orange juice sale in this market. Further, these product categories are not used by Dominick’s as loss-leaders.

\(^5\) Specifically, the wholesale price = \((1 – \text{margin\%}) \times \text{retail price}\). These wholesale price series are computed by the retailer as the weighted average of the amount the retailer paid for all their inventory. For example, if the retailer bought its current stock of frozen concentrate Tropicana 12oz in two transactions, the wholesale price is computed as the average of these two transaction prices. No FIFO or LIFO accounting rules are used in these computations. The effect of these calculations on the accuracy of the wholesale price series is not likely to be large since the inventory turnover in the orange juice category is very fast: frozen orange juice turns over every 6–7 days and refrigerated orange juice turns over every 7–9 days. (The reason for this high turn over rate is the high storage cost of both types of juice.) Since the inventory turns over approximately once a week, the wholesale price series is quite reflective of the current manufacturer wholesale prices. It should be noted also that this wholesale price does not include lumpy payments like slotting allowances. However, our discussion with the managers who set the retail prices indicate that these kind of payments were not common in the orange juice category during the period covered in our study. Further, these managers indicated that they rely on this wholesale price series for making their pricing decisions. The wholesale price series we use were computed using the retail price and margin information. The source of both series is the scanner database.
more aggregate price indices. The availability of actual transaction prices for the same products at two levels of the distribution channel is another unique aspect of this data set.

(3) Manufacturers’ costs: For the manufacturers of the products we study, the cost of orange juice concentrate input constitutes the bulk of the total cost (Ward and Kilmer, 1989). As a measure of this cost we use the spot market price for that week. To arrive at the spot cost, we use the nearest futures price of frozen concentrated orange juice in the commodities’ exchange market.\textsuperscript{6} This nearest futures price is adjusted for storage and carrying costs to compute the spot cost using the cash-and-carry arbitrage formula.\textsuperscript{7} This adjustment was carried out using information provided by the NYCE which uses this method routinely to compute and adjust current and futures prices.\textsuperscript{8}

We use the spot price as a proxy for the price at which the manufacturers purchase the frozen concentrated orange juice.\textsuperscript{9} We believe that the use of this proxy is reasonable for this market. Our reasoning is as follows. Manufacturers can acquire frozen concentrated orange juice in two main ways. First, they can purchase it at current price, which reflects current market supply and demand conditions, from either (a) independent growers, (b) growers participation plans which sell the product together, or (c) cooperatives of orange growers. Second, they can sign a contract with growers. The contract may either (a) specify a price, (b) leave the price open to be determined at the time of delivery, or (c) include a minimum guaranteed price in return for longer term commitment. In addition, the contract may specify the minimum fruit quality, payment basis and scheme, and the quantity. The average share of frozen concentrated orange juice sold through these different arrangements during the 1980s is as follows: 4.5 percent from independent growers, 14.5 percent through participation plans, 47.5 percent from growers cooperatives, and 33.5 percent through contracts with growers (Ward and Kilmer, 1989).\textsuperscript{10} Thus, at least 67 percent of the frozen concentrated orange juice sold is based on market prices which reflect current supply and demand.

\textsuperscript{6}The nearest futures price was collected from the *Wall Street Journal* on Thursday of each week which reports the price set at the Wednesday’s trade. Wednesday’s price data were chosen in order to match them with the price change decision day of the week, which is usually Thursday. These price change decisions are based on variety of information (costs, competitors prices, sales, etc.) the retailers routinely collect for price managers use (Levy, Bergen, Dutta, and Venable, 1997a, 1997b, 1997c, and 1998). The market trades in futures contracts with contract maturity ranging from 2 to 18 months. Citrus Associates, which include the processors, manufacturers, institutional investors, and brokerage firms are the main players in this market.

\textsuperscript{7}Specifically, the storage cost is computed using the interest rate on 6-month treasury bill at that time and monthly carrying cost is based on the information provided by NYCE. Similar procedures are also used in the finance literature (e.g., French, 1986; Fama and French, 1987). The use of nearest futures price as a proxy of the spot price means that once each month there is a possible change from the month \( n \) contract to the month \( n + 1 \) contract which may pose a problem. The adjustment of these series for storage and carrying cost is designed to resolve this problem.

\textsuperscript{8}The computed spot cost was divided by 1600 to get a dollar per ounce price of frozen orange concentrate. The price quoted at NYCE is for orange concentrate level of 57 degree brix. (A brix is a measure of the pounds of solids and the sugar content in one gallon of juice.) From the information provided by the retailer, we found that the brix level for frozen orange concentrate (both national brand and private label) is 41.8 and the brix level for refrigerated juice (both national brand and private label) is 11.7. So we adjusted downwards the NYCE spot price to ensure similar quality as measured by brix solid content per oz.

\textsuperscript{9}The use of spot price as a proxy for manufacturers’ costs is also necessitated by the fact that the market prices at which the manufacturers purchase the frozen concentrated orange juice are not publicly available on a weekly basis.

\textsuperscript{10}These shares are computed as averages of the figures for the 1980–87 period presented in Table 3.3 by Ward and Kilmer (1989).
conditions, and the prices of a large portion of the remaining 33 percent may also be based on market conditions since, as mentioned above, many contracts may leave the price open. Since the spot price reflects current and expected market supply, market demand, and weather conditions, and since, as mentioned above, 2/3 or more of the frozen concentrated orange juice is sold at prices that reflect current market conditions, the spot price and the manufacturers purchase price are correlated (Ward and Kilmer, 1989). In addition, the manufacturers are major traders in the New York Cotton Exchange and therefore, the prices set at this market should be related to the costs incurred by the manufacturers. Finally, it should also be noted, that this cost proxy is still more micro-based than many cost measures that have been used to study price rigidity in the past (such as GNP deflators, CPI, etc.).

(4) **Weekly time series:** The frequency of the time series we use is weekly. This is particularly useful for studying price adjustment with Dominick’s data since pricing at Dominick’s is done on a weekly basis. i.e., the chain changes prices only once a week.11

(5) **Stages of processing:** By collecting data on manufacturers’ costs we are able to study retail reactions to wholesale and upstream cost changes simultaneously. Given the two-stage vertical distribution structure of the market we study, our data set enables us to examine the role of stages of processing in the retail price rigidity, an issue emphasized by Blanchard (1983), Mankiw (1985), Gordon (1990), Blinder (1994), Meltzer (1994), and Basu (1995).12 Further, these data enable us to compare the rigidity of prices across the two channels. This comparison is particularly “clean” since the products compared across the two channels are identical, even the packaging is the same: “Generally this represents transformation in time and space only, since most citrus products are produced in their final consumable form at the packer or processor level” (Ward and Kilmer, 1989, p. 36). The only difference between the two channels of distribution is the sellers’ and buyers’ identity: at the manufacturing level, the sellers are manufacturers and the buyers are the retail stores, while at the retail level, the sellers are retail stores and the buyers are the general public.

(6) **Exogenous cost changes:** With this data, we examine the effect of *exogenous* cost changes on prices almost as if it were a controlled experiment. Changes in retail cost are exogenous with respect to retail price because: (i) the market we study is of a hierarchical nature since the retailer follows the manufacturers and manufacturers follow orange growers in the channel of vertical distribution; (ii) the manufacturers in this

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11Levy, Bergen, Dutta, and Venable (1997a, Table VI) document the actual number of price changes and their frequency for large U.S. supermarket chains. They find that in their sample of representative stores the price changes are usually done on a weekly basis according to the following schedule: prices of advertised general merchandise are changed every Saturday afternoon, prices of advertised grocery—every Tuesday afternoon, prices of general merchandise—every Monday afternoon, prices of grocery—every Sunday afternoon, etc. They find a similar price change schedule at a large chain drugstore (Levy, Bergen, Dutta, Venable, 1997b).

12This is different from the input-output structure emphasized by Gordon (1990), Meltzer (1995), and Basu (1995). As Gordon (1990) suggests, the input-output view of the market organization is better suited for more aggregated (e.g., industry level), and more complex products produced using many inputs. In contrast, here we study individual products, and also the products themselves are simple, produced with few inputs.
study sell nationally, while the retailer we study is one of many regional sellers in the Chicago metropolitan area; and (iii) as an orange juice seller, the retailer is significantly smaller than the national manufacturers. For similar reasons, we argue that the commodity spot cost can be treated as exogenous with respect to the wholesale as well as retail prices, as suggested by Roll (1984) and Baur and Orazem (1994).\footnote{We find no evidence of changes in the market power of the downstream firms over the sample period.}

(7) Cost and price variation: For studying price rigidity, an ideal data set would provide prices of a product over a period of time long enough for there to have been significant change in market conditions. The orange juice price and cost data we use satisfy this requirement. We use weekly data, during which some extreme weather changes affected the orange juice market conditions significantly. Indeed, descriptive statistics reported in Tables 1–5 and the time series plotted in Chart 2 indicate a significant variation in these prices and costs over our sample period. Roll (1984) also observed similar variation in the commodity price of frozen concentrated orange juice.

(8) Constant quality: For studying price rigidity, ideal products would maintain a constant quality throughout the sample period. The products we study satisfy this requirement as well. The quality of orange juice is closely monitored and is generally held unchanged. The quality of orange solids is guaranteed by standardized concentration and minimum "scores" for color, flavor, and defects. The minimum standards for Florida juice are set by the Florida Department of Citrus and the United States Department of Agriculture (USDA).\footnote{For a more detailed description of the minimum Florida and USDA requirements and standards which various types of oranges and orange juice must meet, see Florida Department of Citrus (1994, pp. 64–68).} The juice quality is determined by machines that analyse the sugar and acid content of the juice and estimate the amount of orange solids (which determines the quality and the quantity of the orange juice extracted) in the crop. Frozen concentrated orange juice quality is further controlled by setting upper limits on the amount of sinking and washed pulp solids. Also, the concentrated orange juice needs to pass the gel test which guarantees that no gel pulp will be left after reconstitution.\footnote{For example, a typical frozen concentrate orange juice futures contract may be specified as follows: “U.S. Grade A with a brix value of not less than 51˚ having a brix value to acid ratio of not less than 13.0 to 1 nor more than 19.0 to 1 and a minimum score of 94, with the factor of color and flavor each scoring 37 points or higher, and defects at 19 or better...” (Roll, 1984, p. 867).} In the retail market, the minimum brix content of the frozen concentrated orange juice and of refrigerated orange juice (both national brand and private label) are 41.8˚ and 11.7˚, respectively. Any decrease in these figures would amount to cheating.\footnote{While cheating is believed to be a rare phenomenon in this market, we were able to find one documented case. According to the New York Times (July 27, 1989, section D, p. 14, column 1), on July 25, 1989, a Federal Grand Jury indicted three former owners of Bodine’s Inc., for allegedly selling under 50 different labels a phony frozen concentrated orange juice during the 1978–85 period. According to the indictment, the accused have developed a recipe using beet sugar, corn sugar, monosodium glutamate, and other “low cost, inferior ingredients” and sold the product as 100% frozen concentrated orange juice. The individuals were eventually convicted and sent to 2-year prison terms (Crain’s Chicago Business, March 5, 1990, p. 8). Kroger was one of the supermarket chains later charged for knowingly selling Bodine’s Inc.’s fake juice under its label, a charge which they denied (The New York Times, August 22, 1989, section D., p. 4, column 1).}
(9) **Widely consumed, representative, small staple retail item**: As Hannan and Berger (1991), Neumark and Sharpe (1993), and Ball and Mankiw (1994) indicate, for the purpose of explaining monetary non-neutrality, the most important prices are for those goods which are purchased with money such as small retail items, because the prices of goods bought with credit may not directly affect the demand for money. The groceries sold by this supermarket chain could not be purchased on credit during our sample period. Further, the products we study are purchased by consumers on a weekly basis and are a part of a regular family shopping basket. The annual sales of frozen concentrated orange juice is approximately $1 billion on 170 million gallons of output (Wall Street Journal, July 12, 1990) which makes these economically significant product categories. Thus, it is a representative and widely consumed retail item. In addition, the pricing practices of the specific retail chain we study are representative of many large U.S. retail grocery chains (Chevalier, 1995). Further, supermarket chains account for 70 percent of retail food store sales in the U.S. (Progressive Grocer, 1989).

(10) **No quantity adjustment**: A large-scale quantity adjustment in response to cost changes is unlikely in this market because of the high storage cost of the products studied here. At the manufacturing level, if a contract is signed between growers and processors, the quantity of the product to be delivered is usually specified in advance in either of the two forms: under “production contract” the buyer takes all of the production from a grove, while under a “limit contract” the exact quantity to be delivered is specified. At the retailer level, retailers have pretty good idea about demand (see the next paragraph), making large unplanned inventory adjustments unlikely.

(11) **Stable demand**: The empirical findings reported by Roll (1984), Ward and Kilmer (1989), and studies cited therein indicate that most of the orange juice commodity price volatility at the manufacturing level is due to supply shocks. The studies conducted by Florida Citrus Commission and University of Florida Center for Citrus Research and Education (see, for example, Ward and Kilmer, 1989, and the references cited therein) reach a similar conclusion for the retail level. Cagan (1974, p. 22), in summarizing the existing econometric evidence, also argues that “Empirical studies have long found that short-run shifts in demand have small and often insignificant effect [on prices], and that, instead, costs play a dominant role.” In addition, we searched the relevant trade publications, like Progressive Grocer and Citrus Futures, as well as the Wall Street Journal, the New York Times, and major Midwestern newspapers, and found no

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17 During 1988 there were 30,754 supermarkets in the U.S. and 55 percent of them belonged to chains of eleven or more stores (Chevalier, 1995).

18 In terms of retail inventory management, typical chains usually store the juice (both frozen and concentrate) in metropolitan warehouses. The manufacturers deliver the products to these warehouses about twice a week. The amount of inventory held in these warehouses is on average about 2–3 days supply. Because of the high storage cost, retailers try hard to avoid larger inventory holdings.

19 Okun (1981, p. 176) also states that “… retail trade displays no significant markup responsiveness to shifts in demand.”
evidence suggesting demand changes during the sample period covered in this study. This should not be surprising: variation in orange juice demand is unlikely since orange juice is a staple item that is routinely bought and consumed on a weekly basis, similar to milk and bread. Therefore, in the empirical analysis that follows, we assume that most of the variation in the product prices we study is driven by supply shocks. Thus, we abstract from demand shocks and try to explain all the variation in prices using costs, as in Gordon (1990), Borenstein et al. (1992), and Borenstein and Shepard (1995). The added advantage of the absence of significant demand shocks is that it minimizes the possibility of an endogeneity bias.

3. The Econometric Model

Of the authors who have empirically examined the evidence on cost-price relationships in various markets, most have studied single channel relationships, or at least treated them as separate, and therefore estimate models incorporating various types of distributed lag structures, which are particularly suitable for studying single channel relationships. However, in this paper we are interested in evaluating the dynamic effect of changes in the manufacturer’s commodity input cost and retailer’s cost on the retail price, and in the dynamic effect of changes in the manufacturer’s commodity input cost on manufacturer wholesale price, simultaneously. This spot-to-wholesale-to-retail market organization contains not one, but two channels. Since one cannot exclude the possibility that the spot price may affect the wholesale and retail prices simultaneously, it is preferable to model the dynamic relationship in the two channels simultaneously. Therefore, we use the vector autoregression (VAR) modelling technique.

In this paper we estimate a restricted three-dimensional VAR model. The three variables are the spot cost, the wholesale price, and the retail price. The VAR model we estimate is given by the matrix equation

$$y_t = \alpha + \sum_{i=1}^{\rho} A_i y_{t-i} + \epsilon_t,$$

where \(y_t\) is a \((3 \times 1)\) vector of spot (\(y_1\)), wholesale (\(y_2\)), and retail (\(y_3\)) prices respectively, \(\alpha\) is a \((3 \times 1)\) vector of constants, \(\rho\) is the lag length, \(\epsilon_t\) is a \((3 \times 1)\) vector of white noise residuals, and \(A_i\) is a \((3 \times 3)\) matrix of the VAR coefficients

$$A_i = \begin{bmatrix}
a_{11,i} & a_{12,i} & a_{13,i} \\
a_{21,i} & a_{22,i} & a_{23,i} \\
a_{31,i} & a_{32,i} & a_{33,i}
\end{bmatrix}.$$
The identifying restrictions imposed on the VAR coefficients follow from our economic reasoning which in this particular case is primarily based on the hierarchical, vertical distribution channel structure of the market we are studying. Manufacturers (processors) follow orange growers in the commodities market and retailers follow manufacturers in the distribution channel of the orange juice market. In addition, the manufacturers of orange juice sell nationally, while the retailer we study is one of many regional sellers in the Chicago metropolitan area. Also, as an orange juice seller, the retailer is significantly smaller than the orange juice manufacturers themselves.

Given this vertical distribution channel structure of the orange juice market, we assume that a change in the spot price may affect the wholesale price as well as the retail price. In addition, we expect the wholesale price to affect the retail price. However, we do not expect the retail price to affect the wholesale price or the spot price. Similarly, we do not expect the wholesale price to affect the spot price. Given the hierarchical structure of the spot-to-wholesale-to-retail channel of the orange juice market, and given the decrease in the size of the seller as we move down the channel from spot to wholesale to retail, we believe that these restrictions are sensible.

In terms of the notation used in (1)–(2) above, these identifying restrictions mean that we set \(a_{12,i} = 0, a_{13,i} = 0,\) and \(a_{23,i} = 0,\) which makes the \(A_i\) matrix lower triangular:

\[
A_i = \begin{bmatrix}
 a_{11,i} & 0 & 0 \\
 a_{21,i} & a_{22,i} & 0 \\
 a_{31,i} & a_{32,i} & a_{33,i}
\end{bmatrix}. \quad (3)
\]

Thus, in the three equation VAR we estimate, in the first equation we have the spot price as the dependent variable and its own lags as the right hand side variables, in the second equation we have the wholesale price as the dependent variable and its own lags as well as lags of the spot price as the right hand side variables, and in the third equation we have the retail price as the dependent variable and its own lags as well as lags of the wholesale and spot prices as the right hand side variables. These identifying restrictions impose a block-recursive structure on the VAR coefficients, which makes the spot price \((y_1)\) *exogenous* with respect to the wholesale \((y_2)\) and the retail price \((y_3)\), and the wholesale price \((y_2)\) *exogenous* with respect to the retail price \((y_3)\). To separate the residuals of the estimated VAR into orthogonalized innovations for the purpose of structural identification of the model, we impose on them a set of restrictions identical to the restrictions imposed on the VAR coefficients.

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22 These exogeneity assumptions are similar to the assumptions frequently employed in the empirical industrial organization and in the empirical macroeconomic literature when researchers rule out the possibility of some disaggregated variable, for example, individual firm’s balance sheet, to affect more aggregate behavior, for example, industry sales (Pagan, 1993; Gilchrist and Zakrajsek, 1995; and Zha, 1996).

23 A VAR model with linear restrictions of the type employed here is often called a *subset* VAR (Lütkepohl, 1991). In the terminology of Zha (1996), the model we estimate here is *strongly contemporaneous block recursive*.

24 The findings reported by Roll (1984) and Baur and Orazem (1994) also support these exogeneity assumptions.
In order to quantify the idea of dynamic price adjustment to cost changes, we present the cumulative impulse responses instead of the usual impulse responses. All three variables we use are price variables measured in the same units, dollars per brix solid oz. Therefore, to make the interpretation of the results more intuitive, we convert the vertical axis scale of the impulse response function into dollars by appropriately adjusting the estimated impulse response and the corresponding confidence interval figures. Thus, instead of the common practice of presenting the response of price to a one standard deviation shock in cost, we present the response of price in dollars to a one dollar shock in cost. We also present the variance decomposition of the series. Along with the estimated impulse response and variance decompositions we also report corresponding 90% confidence intervals. These were computed using the asymptotic distribution results reported by Lütkepohl (1990).

As an example, the time series of spot cost, wholesale price, and retail price of refrigerated Tropicana, 64oz, are plotted on Chart 2. In most of these series there are systematic sales and promotions approximately every three to five weeks as indicated by the frequent price reductions in the plot. These systematic promotional patterns are the standard practice for retailers of these and similar products. For the purpose of our analysis these promotional sale activities can be considered exogenous and therefore the estimation results should be unbiased. The sales may, however, raise the noise level.

4. Results on Price Rigidity at the Retail Level

In section 4.1 we start with a discussion of the first notion of price rigidity. Next, in section 4.2 we study retail price rigidity by examining the dynamic reaction of prices to cost changes. Finally, in section 4.3 we evaluate the importance of stages of processing in generating price rigidity by examining whether retailers respond to changes in upstream cost when setting retail prices.

25 Following Lütkepohl’s (1990) suggestion, the orthogonalization of the innovations used in the impulse response analysis are achieved by using the residuals of the restricted model (3).

26 The lag length, \( p \), of the VAR we estimate, was chosen using lag selection criteria. We looked at four criteria: Final Prediction Error (FPE), Akaike’s Information Criterion (AIC), Hannan-Quinn Criterion (HQC), and Schwarz Criterion (SC). The FPE and the AIC indicated optimal lag length of six. The HQC and the SC suggested optimal lag length of two. We have decided to choose a lag length of six since simulation studies cited by Lütkepohl (1990, 1991) show that FPE and AIC have better small sample properties in the sense that they choose the correct lag length more often than HQC and SC. This choice may not be costless, however. This is because, as Lütkepohl (1990) shows, if a VAR order is chosen too large, this may result in imprecise coefficient estimates leading to large standard errors of the impulse response and variance decomposition functions. It turns out that the small sample properties of these standard errors do not differ much from the properties of the standard errors estimated based on more commonly used Monte Carlo integration, bootstrap, or other resampling methods (Lütkepohl, 1990 and 1991). However, the computational simplicity and the speed of the asymptotic distribution method makes this approach significantly cheaper (Lütkepohl, 1990). See Sims and Zha (1995) and Zha (1996) for a Bayesian perspective on this.

27 The model was estimated with the variables measured in first differences since the standard ADF unit root test results (not reported to save space) indicate that the price and costs series we use are \( I(1) \).

28 In the discussions that follow we do not present the estimation results for the spot price equation, which is the first equation of the VAR system (1), where the spot price depends only on its own lagged values. This is because understanding the determinants of the spot prices of the orange juice are beyond the scope of this paper. For a study addressing this specific question, see Roll (1984). For the goal of studying the rigidity/flexibility of the wholesale and retail prices, the important point to remember is that spot prices can plausible be thought exogenous with respect to the wholesale and retail prices, and the wholesale prices can be thought exogenous with respect to the retail prices. Therefore, we argue, that spot price belongs to the
4.1. Measures of retail price rigidity based on frequency of price changes

Let us consider the first notion of price rigidity by looking at some descriptive statistical measures of the original (not moving averaged) retail price data. These include sample mean and variance, number of changes, average number of weeks between changes, and average, maximum, and minimum changes in dollars and in percents. Table 4 presents these statistics for the retail prices of refrigerated juice and Table 5 for the retail prices of frozen concentrated juice. All prices and costs in these tables are measured in dollars/oz. According to these tables, the actual number of price changes observed during the 88-week period covered in this study is between 38–51 for 64oz and between 22–30 for the 96oz refrigerated juice. This implies that the average number of weeks between consecutive price changes for the 64oz refrigerated juice is about 1.6–2.2 weeks. For the 96oz refrigerated juice, the average number of weeks between consecutive price changes is about 2.8–3.8 weeks. For frozen concentrated orange juice, the actual number of price changes is between 36–39 for 12oz and between eight to twelve for the 16oz, with the exception of Tropicana 16oz which seems to behave in a way similar to Tropicana 12oz. This implies that the average number of weeks between consecutive price changes of 12oz frozen concentrated juice (and Tropicana 16oz) is slightly above two weeks. For the 16oz juice, the average number of weeks between consecutive price changes is about seven to ten weeks.

Overall, judging from such frequent changes, the retail prices of orange juice, at least of the standard size, indicate a remarkable flexibility in comparison to the figures cited in other studies for prices of other product categories. For example, Cecchetti (1985) finds that newsstand magazine prices remain unchanged for two to five years. Kashyap (1995) reports that mail order companies hold their catalog prices unchanged for six to twenty four months.30

4.2.1 Cost-based evidence on retail price rigidity

We begin by presenting VAR estimation results where we study how changes in retailer’s costs affect the retail prices over time. The cumulative impulse response functions depicting the dynamic effect of direct cost (i.e., wholesale price) changes on retail prices are shown in the middle panels (b and e) of Figures 1.1–1.6. Figures 1.1–1.3 display the cumulative impulse responses for the refrigerated juice and Figures 1.4–1.6 for the frozen concentrated juice. On each figure, the left hand side column displays the impulse response for the standard size and the right hand side column for the off-standard size. These right hand side of the wholesale and retail price equations. The first equation is included in the model only for the sake of simplicity of the formulation of the block recursive system. Since the model is estimated equation by equation, this inclusion does not drive, nor affect, the results we report here for the wholesale and the retail prices. The estimation results (that is, the impulse response and the variance decomposition) for the first equation are available upon request. This somewhat simplistic comparison (and similar comparisons made in the paper further below) come to emphasize the extend of heterogeneity in the rigidity of prices across different products. Given the variation in the institutional characteristics of different markets, this heterogeneity perhaps should not be surprising. Understanding the reasons for these kind of heterogeneities, however, remains largely unexplored (Gordon, 1990; Caplin, 1993; and Meltzer, 1995). See Bergen, Dutta, and Levy (1996) for a recent attempt.
cumulative impulse response functions represent the cumulative response of the price in dollars to a one-dollar shock in the cost.

The notion of price rigidity is most relevant in the short run, since in the long run prices are flexible. Therefore, we define price rigidity as an incomplete response of prices to cost shocks in the short run. Recall that the traditional economic definition of long run is the time horizon it takes the particular market to completely adjust to all the information. To operationalize this definition, we communicated with various orange juice market participants, such as the retail buyer, some manufacturers, and Florida Citrus Commission officials. These conversations suggest that a twelve to sixteen week period or longer would be considered long run (i.e. the time horizon it takes this market to completely adjust to all the information) and that an eight-week period or shorter would be considered short run. Using this information as the guideline, we define the first eight-week period after the occurrence of the shock as the short run and twelve-week and longer horizon as the long run.

Although the use of cumulative impulse response functions makes the empirical analysis of price rigidity simple since it enables us to compare and rank the cumulative reactions of prices to cost shocks (e.g., the smaller the cumulative response, the more rigid the prices are), it is still necessary to adopt some ad hoc criteria for establishing the rigidity/flexibility of prices. Since picking any particular cut off point of the cumulative impulse response function is difficult to defend, we consider two possible extreme values of pass through, one corresponding to a complete price flexibility and the other corresponding to a complete price rigidity. If prices adjust completely to cost shocks in the short run (i.e., one-dollar increase in cost leads to a cumulative one-dollar increase in price), which is what we would expect under perfect competition, then we say that prices are flexible. If prices do not adjust to cost shocks in the short run, then we say that prices are rigid.

Thus, two specific values of the cumulative impulse response function we consider below are zero and one. If the 8th week confidence interval of the cumulative impulse response function contains one but not zero (as, for example, in the case of refrigerated Tropicana, 96oz, wholesale-to-retail channel, Figure 1.1e), then the null of a full short-run price adjustment cannot be rejected. This would imply short-run price flexibility. If the confidence interval contains zero (or any figure between zero and one) but not one in the short run (as, for example, in the case of refrigerated Tropicana, 96oz, spot-to-wholesale channel, Figure 1.1d), then we interpret this as evidence of short-run price rigidity.31 In the cases where the 8th week confidence interval of the cumulative impulse response function is too wide and contains both zero and one (as, for example, in the case of refrigerated Tropicana, 64oz, spot-to-retail channel, Figure 1.1c), then we

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31 It should be noted however, that the choice of these cut off points is not problem free. For example, the passthrough may be larger or smaller than 1 depending on the extent of competition, industry concentration, and market power. Also, using zero as a lower bound may be extreme in the sense that it may be unlikely to expect no passthrough after 8 weeks. The difficulty we face is that picking any other values for these cutoff points seem at least as (and may be even more) difficult to defend.
consider the central tendency of the true impulse response by looking at a more narrow confidence interval (for example, 1.00 standard error rather than 1.64 standard error). Since this is a weaker test of rigidity/flexibility, we denote flexible or rigid outcomes in these situation as either “tending toward flexibility” or “tending towards rigidity.” In Table 6 we have summarized these results for all 36 impulse response functions reported in this paper. For each channel, i.e., for each row, we have twelve impulse response functions which correspond to the twelve products we study.

According to the impulse response functions, the retail prices are flexible in terms of their response to direct cost (i.e., wholesale price) changes. From the middle row of Table 6 we can see that in nine out of twelve cases the retail prices are flexible according to our definition, and in only three cases they exhibit rigidity. As the middle panels of Figures 1.1–1.6 suggest, in many cases the adjustment occurs within three to six weeks from the time the shock occurs.

The variance decomposition results for the retail prices are presented in Figures 1.7–11.12, panels b and e. On each figure, the left hand side column displays the variance decomposition for the standard size and the right hand side column for the off-standard size. According to the plots, the estimated variance decomposition figures tend to settle down at around eight-week lag, supporting our choice of 8th week period as a reasonable cut-off point for specifying the short-run period.

These variance decomposition results are in general consistent with the corresponding impulse response function results. They indicate that in eight of the twelve cases the contribution of the wholesale price innovations to the retail price forecast error variance is relatively large, between 10 to 35 percent, and statistically significant. In four other cases the variance decomposition indicates small or statistically insignificant effect of wholesale price innovations on retail prices. Thus, the results in general suggest that wholesale prices play a role in the determination of retail prices.

4.2.2. Discussion

In sum, we find that retail prices are very flexible in terms of both notions of price rigidity: (i) they change frequently, and (ii) they respond quickly (often within three to six weeks) and fully to changes in costs. This is an indicator of a remarkable flexibility of retail prices. For comparison purposes, it should be mentioned that Blinder (1994) reports an average lag of three to four months (twelve to sixteen weeks) in the response of prices to cost shocks. Other studies that use micro-level data of final prices, such as Cecchetti

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32 For example, in the case of refrigerated Tropicana, 64oz, spot-to-retail channel, Figure 1.1c, the 8th week 1.64 standard deviation confidence interval contains both, zero and one, which makes it difficult to interpret. However, if we consider 1.00 standard deviation confidence interval, then zero does not fall in the 8th week confidence interval anymore, but one still remains. Therefore, we describe this case as “tending towards flexibility,” which reflects the idea that it is only the central tendency we are describing given the width of confidence interval: it is more likely that the true value will tend towards one than zero.

33 Two cases, frozen Tropicana, wholesale-to-retail, Figure 1.4e, and frozen Heritage House, wholesale-to-retail, Figure 1.6b, appear to produce anomalous result: the point estimate of the impulse response functions is negative for most of the 26-week period. Both confidence intervals, however, contain the entire zero line and hence, the true values of the impulse response function statistically do not differ from zero.

34 The share of the forecast error variance of a variable accounted for by its own innovations are not shown to save space.
(1986) and Kashyap (1995), find even more delayed response of prices to cost shocks. Since our product categories are widely used and representative of many typical retail items, this finding raises the possibility that prices of many other consumer goods which share similarities with the products we study may also exhibit significant flexibility.

The main explanation for this finding of flexibility is that the retail market we are studying seems to be very competitive. There are many players in this market and no single chain dominates it. Our retail chain, Dominick’s, competes with Jewel, Cub Food, Eagle, Aldi, Walts, and local cooperatives, to name a few. In general, price competition is very intense in the retail grocery industry (Consumer Reports, 1993), with frequent price wars (Calantone, Droge, Litvack, and DiBenedetto, 1989), and this price competition seems to have escalated over the years in the retail grocery market (Progressive Grocer, 1992 and 1993). The margin for the retailer is small, about one to three percent, which is a further indication of the intensity of competition in this industry (Montgomery, 1994). Theoretical studies (Okun, 1981; Dornbusch, 1987; Carlton, 1986 and 1989; Rotemberg, 1987) show that price flexibility is related to the degree of competition. For example, Dornbusch (1987) shows that a greater degree of price competition will lead to more price flexibility. Thus, the finding of flexibility of retail prices, as measured by their response to changes in direct costs the retailer incurs, may be explained by the highly competitive environment in which the retailer is operating. This explanation is consistent with the results reported by Levy, et al. (1997a), who find that supermarket chains of the type studied here each week change prices of as many as 15 percent of the products they carry (prices of about 4,000 of the 25,000 products carried), in spite of the fact that their cost of changing prices comprises over 35 percent of their net margin.

4.3.1. Further evidence on retail price flexibility and its relation to stages of processing

We now discuss VAR estimation results where we study how changes in upstream spot commodity costs affect the retail prices over time. According to the estimated impulse response functions, which are reported in the bottom panels of Figures 1.1–1.6, the retail prices tend to be flexible in response to changes in upstream costs. From Table 6 we can see that in ten of the twelve cases retail prices are flexible according to our definition (in seven cases they are strictly flexible, and in three cases they tend towards flexibility) and in only two cases do prices exhibit rigidity (one case of rigidity and one case of tendency towards rigidity). Thus, according to these figures, the retail prices respond to upstream commodity cost changes and the adjustment process seems to be rather quick, often within four to six weeks.

The impact of the spot price on retail price is also evident if we look at the variance decomposition results reported in panels c and f of Figures 1.7–1.12. The figures indicate that between ten to twenty percent of the retail price forecast error variance is due to spot price innovations. With two exceptions, the

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35 See also Levy et al. (1997c).
estimated figures are all statistically significant.

In the cases where the contribution of the wholesale price to retail price is small and statistically insignificant, the contribution of the spot price is large and significant, as the plots in panels c and f of Figures 1.7–1.12 indicate. Perhaps, the presence of the spot price in the retail price equation is leading to this result. Overall, both costs seem to play some role in the sense that the retailer seems to take both indirect and direct cost changes into account when setting their retail prices. Taken as a whole, the impulse response functions and the variance decomposition results suggest that both the spot costs and wholesale prices affect final retail prices.

### 4.3.2 Discussion

The findings that downstream prices may be responding to upstream cost changes may be the most striking finding we report in this study. These findings can be related to the role of stages of processing in price flexibility. Studies, for example, Taylor (1980), Blanchard (1983), Mankiw (1985), Gordon (1990), Blinder (1994), and Basu (1995), have shown that markets with vertical hierarchical structure may exhibit slow adjustment process of prices to cost shocks originating upstream.\(^\text{36}\) We find that this does not really happen in our data in spite of the fact that the market we study has a clear vertically hierarchical structure, spot-to-wholesale-to-retail. This may be because we study here individual products which are produced using only few inputs and which flow through only two stages of processing. Gordon (1990) suggests, in such an environment a quick response of price is expected. The stages-of-processing model of Blanchard (1983) makes a similar prediction: the smaller the number of stages of processing, the more flexible prices are. The market we study consists of only two stages of processing, which seem not be a sufficient barrier to retail price adjustments.

A possible explanation for this finding is that the information of cost changes that occur upstream are readily available to retail price setters. This is because the behavior of frozen concentrate orange juice contract prices at the NYCE are published daily in the general financial media. The big commodity cost increase observed in our data during December 1989 (observations 16–20) was caused by a freeze in Florida which significantly damaged not only the fruit on trees, but also the trees themselves. The damage was so big that Florida Governor in December 29, 1989 declared entire state of Florida a disaster area. This freeze made national headlines and it is likely that the average consumer was also aware of it.

### 5. Results on Price Rigidity at the Manufacturer Level

In this section we start with a discussion of the findings based on the first notion of price rigidity in section 5.1. Next, in section 5.2 we study intermediate goods price rigidity by examining the dynamic reaction of wholesale prices to commodity cost changes.

\(^\text{36}\) Blinder’s (1994) survey study concludes that most price setters surveyed do not consider the existence of channels or stages of processing in production a reason for their lack of price adjustment.
5.1. Measures of wholesale price rigidity based on frequency of price changes

Tables 2 and 3 present descriptive statistical measures for the original (not moving averaged) wholesale prices of refrigerated and frozen concentrated orange juice, respectively. According to the tables, the actual number of wholesale price changes observed during the 88-week period is between 40–55 for 64oz and between 21–47 for the 96oz refrigerated juice. This implies that the average number of weeks between consecutive price changes of 64oz refrigerated juice is about 1.5–2.1 weeks. For the 96oz refrigerated juice, the average number of weeks between consecutive price changes is about 1.8–3.9 weeks. For frozen concentrated orange juice, the actual number of price changes is between 31–35 for 12oz (with the exception of Tropicana 12oz) and between 13–24 for the 16oz, (with the exception of Tropicana 16oz). This implies that the average number of weeks between consecutive price changes of 12oz frozen concentrated juice is about two to three weeks, with the exception of Tropicana 12oz whose price seems to change every four to five weeks. For the 16oz juice, the average number of weeks between consecutive price changes is about three to six weeks, with the exception of Tropicana 16oz whose price seems to change every twelve weeks.

Thus, judging from such frequent changes, the wholesale prices of orange juice, at least of the standard size, are also very flexible, especially in comparison to the figures cited in other studies of intermediate goods prices for other product categories. For example, Carlton (1986) finds that prices of various types of intermediate goods in many manufacturing industries remain unchanged for almost a year and sometimes even longer. According to Blinder (1994), 55 percent of the firms in his sample change prices no more than once a year.

5.2.1. Cost-based Evidence on Wholesale Price Rigidity

Now we present VAR estimation results where we study how changes in spot commodity costs affect the wholesale prices over time. The cumulative impulse response functions depicting the dynamic effect of spot commodity cost changes on wholesale prices are shown in the top panels (a and d) of Figures 1.1–1.6. According to the impulse response functions, the wholesale price tends to be less flexible in response to cost changes in comparison to the retail price. According to Table 6 in six of the twelve cases wholesale prices are rigid in the short run according to our definition, and in six cases they are flexible. Thus, according to the impulse response functions, wholesale prices of one half of the products studied here do not respond fully to changes in commodity cost. The extent of the price rigidity found in this channel is particularly significant for frozen Tropicana, Figures 1.4a and 1.4d. In sum, the impulse response functions at this channel suggest that at the manufacturing level more prices are rigid in comparison to the retail level.

The results of variance decomposition reported in panels a and d of Figures 1.7–1.12 indicate that in five of the twelve cases the contribution of the spot price innovations to the wholesale price forecast error
variance is small and statistically insignificant. In the remaining seven cases the figures indicate a relatively large and statistically significant effect. The small and statistically insignificant effect of spot cost on the wholesale price for Frozen Tropicana, Figures 1.10a and 1.10d, is evident here too.

5.2.2. Discussion

Perhaps the most interesting finding in this section is that we find evidence of more price rigidity in response to cost shocks in the intermediate goods level of the market. This, even though wholesale prices change frequently and therefore exhibit flexibility according to the first measure of price rigidity. Our evidence provides support for Warner and Barsky’s (1995) contention that the mere finding of individual price volatility is not inconsistent with the existence of price rigidities. There may, in fact, be interesting aspects of price rigidity in markets where prices do change frequently. At a minimum, this suggests the importance of defining and measuring price rigidity in terms of price response to cost or demand changes as suggested by Blinder (1991) and Carlton and Perloff (1994).

This price rigidity can be explained by the limited degree of competition, and the extent of contracting and long term relationships found in these markets. There are few national brands that control significant shares of the orange juice market. For example, during 1991, the market share of Tropicana was 21.6 percent and that of Minute Maid was 21.4 percent (Freedman, 1991), while the rest of the market was shared by private labels and smaller brands. Ward and Kilmer (1989, p. 41) state that, “data on the market structure among processors indicate that the industry is oligopolistic.” This suggests that the manufacturer level of the channel is less competitive in comparison to the retail level of the channel, and therefore should exhibit more price rigidity.

A presence of long-term explicit nominal contracts can also lead to the price rigidity. In the frozen concentrated orange juice market, the manufacturers of national brands often have long-term contractual arrangements with their suppliers (Freedman, 1991). For example, “A common practice among many manufacturers and retail chains is to establish verbal contracts to purchase a fixed supply of private label citrus over the season” (Ward and Kilmer, 1989, p. 49). Similarly, “A large share of brand sales are made through contractual arrangements with the major food retail chains” (Ward and Kilmer, 1989, p. 36). Thus, the existence of these contracts may also help explain the rigidity we observe at this level of the channel. In contrast, no such explicit contracts exist between retailers and their customers. Therefore, we would expect to find more rigidity at the manufacturing level in comparison with the retail level.

The orange juice manufacturers studied here have long term relationships with retailers which could be another source of price rigidity. For example, according to Ward and Kilmer (1989), long term relationships are an important aspect of transactions between these manufacturers and retailers.

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37 See, for example, Fischer (1977) and Taylor (1980).
38 One advantage of such a long-term relationship for retailers is that retail buyers are often eligible to purchase given amounts
finding of rigidity at the manufacturing level should not be surprising since it is an intermediate goods market. In his study of intermediate goods transactions prices, Carlton (1986) also finds significant price rigidity and suggests that these long term relationships can contribute to price rigidity. Williamson (1975) also states that the impediment to changing price may be that the buyer or seller could feel the other side is taking advantage of him. Okun (1975, 1981) and Haddock and McChesney (1994) also suggest the importance of these kinds of considerations. In contrast, individual long-term relationships are not as common between large supermarket retailers and their customers. Given the volume of sales and the large number of customers the retailers serve, it is difficult to individualize these relationships. Therefore, we would expect to find more rigidity at the manufacturing level in comparison with the retail level.

6. Conclusions

In this study we empirically examine the extent of price rigidity in two consumer good product categories for twelve individual products using a unique data set that consists of retail prices, wholesale prices, and manufacturers’ costs. We find that retail prices exhibit flexibility in terms of both notions of price rigidity considered in this paper: they change frequently, and they respond quickly and fully to changes in costs. Moreover, we find that retail prices respond not only to direct costs, but also to upstream costs which further reinforces the degree of retail price flexibility. This is a significantly greater degree of price flexibility than has been reported in the existing studies of final good prices and suggests that retail price flexibility may be more prevalent than currently believed. The finding that stages of processing do not inhibit price flexibility for these products is important because the existing theoretical models of price adjustment usually do not consider this kind price response to indirect or upstream cost shocks. This also suggests that more empirical work needs to be done using micro level data with explicit consideration of the interactions between multiple levels of the channel through which products flow.

At the manufacturing level we find evidence that wholesale prices may be more rigid than appears on the surface. Specifically, we find that even though wholesale prices change frequently, they still exhibit rigidity in reaction to cost changes. This suggests that price rigidity may be an important phenomenon even under conditions of changing prices, and echoes Warner and Barsky’s (1995) suggestion that the mere finding of individual price volatility is not inconsistent with the existence of price rigidities. This raises the possibility that price rigidity may be hiding under the surface of many markets that may seem at first glance flexible. At a minimum, this finding suggests the importance of defining and measuring price rigidity as price responses to cost or demand changes.

39 The findings reported by Basu (1995) are also consistent with the rigidity of intermediate goods prices.
Finally, we find a wide variation in the degree of price rigidity, from rigidity in wholesale prices all the way to flexibility in retail prices.\textsuperscript{40} We explain this variation by documenting the differences in the competitive, contracting, and long-term relationship structures of these two levels of the channel. This variation suggests that the theoretical assumptions of complete price rigidity or complete price flexibility made in many widely used models may not be accurate characterization of all markets. Therefore, at the theoretical level, macroeconomic models which allow prices of some goods to be rigid and others—flexible, as recently done, for example, by Ohanian and Stockman (1994a, 1994b) may be a promising route to pursue. At the empirical level, this variation suggests the importance of studying heterogeneity in price rigidity to determine which industries, and which markets have rigid/flexible prices.

These findings point to various future research questions for which this type of data can be particularly useful. For example, the finding that retail prices respond not just to their direct costs but also to these upstream manufacturers’ costs reinforces the results on retail price flexibility, and suggests that it is important to view prices in the context of all costs, both direct and indirect, to fully understand the response of prices to cost or demand shocks. Therefore, more empirical work is needed to fully explore the interactions between multiple levels of the market through which products flow using other micro level data sets with particular attention to the content of the information set that price setters have at different levels, as suggested by Blanchard (1987), Gordon (1990), and Meltzer (1994). We only study the cost-price relationship for two product categories and for a single retail chain. The product categories we study (frozen concentrate and refrigerated orange juice) are widely used and representative of many typical retail items. Further, the pricing practices of Dominick’s retail chain are representative of many large U.S. retail grocery chains. Nevertheless, future research should examine these issues across other product categories and other retail stores. An additional question one could study with our data is how prices respond to cumulative cost changes, as, for example, in Cecchetti (1986). Also, the data set of the type used here can be used to evaluate which of the existing theories of cost of changing price (e.g., fixed cost vs convex cost) fits the retail market we study best, as, for example, in Sheshinski, Tishler, and Weiss (1981), Lieberman and Zilberfarb (1985), Danziger (1987), Rotemberg (1987), and Kashyap (1995). At the theoretical level, the finding that prices may be responding not only to direct costs but also to upstream costs, suggests that studying models which accommodate such an indirect cost-shock passthrough may be a potentially fruitful research direction to pursue.

\textsuperscript{40}Following several readers’ suggestion, we have estimated our model using moving averaged data to smooth the effect of the promotional sales activities. For this we applied a simple moving average of order five to our data. The choice of the width of the moving average window was dictated by the pattern of the sale activities. The data indicates that typically a product goes on sale approximately once during a four-week period. Therefore, using a window width of three would not always suffice to spread the sales effect onto non-sale periods. On the other hand, a window width of seven would spread the sales effect over too wide an interval. Thus the choice of five. Following a similar line of reasoning, and for the sake of consistency, we have adjusted the wholesale price series using the same moving average. It should be mentioned, however, that sales activity at the wholesale level as reflected in the cost data is not as heavy as at the retail level. The results, reported in Table 7, are in general similar to what we find when we use original data, as reported in Table 6. The main difference between the two sets of results is that the impulse response functions we get when we use moving averaged series are “prettier” in the sense that they are smoother. These plots are available upon request.
References


Lieberman, Yehoshua and Ben-Zion Zilberfarb (1985), “Price Adjustment Strategy under Conditions of


Table 1. Descriptive statistics of the spot price (dollars/oz)

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ($)</td>
<td>0.0692</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0158</td>
</tr>
<tr>
<td>No. of Changes</td>
<td>71</td>
</tr>
<tr>
<td>Average No. of Weeks between Changes</td>
<td>1.17</td>
</tr>
<tr>
<td>Average Absolute Change ($)</td>
<td>0.0026</td>
</tr>
<tr>
<td>Average Absolute Change (%)</td>
<td>4.00</td>
</tr>
<tr>
<td>Maximum Absolute Change ($)</td>
<td>0.01</td>
</tr>
<tr>
<td>Maximum Absolute Change (%)</td>
<td>17.36</td>
</tr>
<tr>
<td>Minimum Absolute Change ($)</td>
<td>0.0003</td>
</tr>
<tr>
<td>Minimum Absolute Change (%)</td>
<td>0.59</td>
</tr>
</tbody>
</table>
Table 2. Descriptive statistics of the wholesale prices of refrigerated orange juice (dollars/oz)

<table>
<thead>
<tr>
<th>Brand Size</th>
<th>Heritage House 64oz</th>
<th>Minute Maid 64oz</th>
<th>Tropicana 64oz</th>
<th>Heritage House 128oz</th>
<th>Minute Maid 96oz</th>
<th>Tropicana 96oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ($)</td>
<td>0.0120</td>
<td>0.0273</td>
<td>0.1026</td>
<td>0.0217</td>
<td>0.0319</td>
<td>0.0373</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0035</td>
<td>0.0030</td>
<td>0.0026</td>
<td>0.0030</td>
<td>0.0034</td>
<td>0.0041</td>
</tr>
<tr>
<td>No. of Changes</td>
<td>55</td>
<td>40</td>
<td>49</td>
<td>47</td>
<td>21</td>
<td>47</td>
</tr>
<tr>
<td>Average No. of Weeks between Changes</td>
<td>1.51</td>
<td>2.08</td>
<td>1.69</td>
<td>1.76</td>
<td>3.95</td>
<td>1.76</td>
</tr>
<tr>
<td>Average Absolute Change ($)</td>
<td>0.0016</td>
<td>0.0013</td>
<td>0.0014</td>
<td>0.0007</td>
<td>0.0013</td>
<td>0.0022</td>
</tr>
<tr>
<td>Average Absolute Change (%)</td>
<td>8.56</td>
<td>4.96</td>
<td>5.37</td>
<td>3.62</td>
<td>4.11</td>
<td>6.31</td>
</tr>
<tr>
<td>Maximum Absolute Change ($)</td>
<td>0.0090</td>
<td>0.0075</td>
<td>0.0061</td>
<td>0.0030</td>
<td>0.0036</td>
<td>0.0104</td>
</tr>
<tr>
<td>Maximum Absolute Change (%)</td>
<td>60.13</td>
<td>27.05</td>
<td>24.05</td>
<td>13.96</td>
<td>11.71</td>
<td>29.59</td>
</tr>
<tr>
<td>Minimum Absolute Change ($)</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.0002</td>
</tr>
<tr>
<td>Minimum Absolute Change (%)</td>
<td>0.63</td>
<td>0.52</td>
<td>0.59</td>
<td>0.50</td>
<td>0.53</td>
<td>0.64</td>
</tr>
</tbody>
</table>
Table 3. Descriptive statistics of the wholesale prices of frozen concentrated orange juice (dollars/oz)

<table>
<thead>
<tr>
<th>Brand Size</th>
<th>Heritage House 12oz</th>
<th>Minute Maid 12oz</th>
<th>Tropicana 12oz</th>
<th>Heritage House 16oz</th>
<th>Minute Maid 16oz</th>
<th>Tropicana 16oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ($)</td>
<td>0.0784</td>
<td>0.1021</td>
<td>0.0854</td>
<td>0.0724</td>
<td>0.1038</td>
<td>0.0865</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0102</td>
<td>0.0111</td>
<td>0.0131</td>
<td>0.0107</td>
<td>0.0119</td>
<td>0.0128</td>
</tr>
<tr>
<td>No. of Changes</td>
<td>35</td>
<td>31</td>
<td>19</td>
<td>13</td>
<td>24</td>
<td>7</td>
</tr>
<tr>
<td>Average No. of Weeks between Changes</td>
<td>2.37</td>
<td>2.67</td>
<td>4.37</td>
<td>6.38</td>
<td>3.46</td>
<td>11.85</td>
</tr>
<tr>
<td>Average Absolute Change ($)</td>
<td>0.0048</td>
<td>0.0038</td>
<td>0.0065</td>
<td>0.0055</td>
<td>0.0054</td>
<td>0.0011</td>
</tr>
<tr>
<td>Average Absolute Change (%)</td>
<td>6.79</td>
<td>3.77</td>
<td>8.13</td>
<td>7.34</td>
<td>5.41</td>
<td>12.72</td>
</tr>
<tr>
<td>Maximum Absolute Change ($)</td>
<td>0.0167</td>
<td>0.0162</td>
<td>0.0203</td>
<td>0.0124</td>
<td>0.0222</td>
<td>0.0241</td>
</tr>
<tr>
<td>Maximum Absolute Change (%)</td>
<td>25.22</td>
<td>18.09</td>
<td>30.61</td>
<td>14.32</td>
<td>24.99</td>
<td>28.45</td>
</tr>
<tr>
<td>Minimum Absolute Change ($)</td>
<td>0.0010</td>
<td>0.0008</td>
<td>0.0008</td>
<td>0.0005</td>
<td>0.0009</td>
<td>0.0005</td>
</tr>
<tr>
<td>Minimum Absolute Change (%)</td>
<td>1.35</td>
<td>0.72</td>
<td>0.82</td>
<td>0.72</td>
<td>0.87</td>
<td>0.68</td>
</tr>
</tbody>
</table>
Table 4. Descriptive statistics of the retail prices of refrigerated orange juice (dollars/oz)

<table>
<thead>
<tr>
<th>Brand Size</th>
<th>Heritage House 64oz</th>
<th>Minute Maid 64oz</th>
<th>Tropicana 64oz</th>
<th>Heritage House 128oz</th>
<th>Minute Maid 96oz</th>
<th>Tropicana 96oz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ($)</td>
<td>0.0322</td>
<td>0.0405</td>
<td>0.0383</td>
<td>0.0344</td>
<td>0.0474</td>
<td>0.0545</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0085</td>
<td>0.0079</td>
<td>0.0068</td>
<td>0.0046</td>
<td>0.0049</td>
<td>0.0068</td>
</tr>
<tr>
<td>No. of Changes</td>
<td>38</td>
<td>43</td>
<td>51</td>
<td>27</td>
<td>30</td>
<td>22</td>
</tr>
<tr>
<td>Average No. of Weeks between Changes</td>
<td>2.18</td>
<td>1.93</td>
<td>1.63</td>
<td>3.07</td>
<td>2.77</td>
<td>3.77</td>
</tr>
<tr>
<td>Average Absolute Change ($)</td>
<td>0.0130</td>
<td>0.0119</td>
<td>0.0111</td>
<td>0.0046</td>
<td>0.0044</td>
<td>0.0106</td>
</tr>
<tr>
<td>Average Absolute Change (%)</td>
<td>45.23</td>
<td>30.99</td>
<td>30.64</td>
<td>14.57</td>
<td>9.18</td>
<td>21.61</td>
</tr>
<tr>
<td>Maximum Absolute Change ($)</td>
<td>0.0266</td>
<td>0.0184</td>
<td>0.0172</td>
<td>0.0117</td>
<td>0.0083</td>
<td>0.0188</td>
</tr>
<tr>
<td>Maximum Absolute Change (%)</td>
<td>99.96</td>
<td>47.90</td>
<td>55.29</td>
<td>40.66</td>
<td>17.10</td>
<td>40.64</td>
</tr>
<tr>
<td>Minimum Absolute Change ($)</td>
<td>0.0016</td>
<td>0.0016</td>
<td>0.0027</td>
<td>0.0008</td>
<td>0.0016</td>
<td>0.0004</td>
</tr>
<tr>
<td>Minimum Absolute Change (%)</td>
<td>5.43</td>
<td>3.94</td>
<td>6.96</td>
<td>2.02</td>
<td>3.14</td>
<td>0.69</td>
</tr>
<tr>
<td>Brand Size</td>
<td>Heritage House 12oz</td>
<td>Minute Maid 12oz</td>
<td>Tropicana 12oz</td>
<td>Heritage House 16oz</td>
<td>Minute Maid 16oz</td>
<td>Tropicana 16oz</td>
</tr>
<tr>
<td>------------</td>
<td>---------------------</td>
<td>-----------------</td>
<td>---------------</td>
<td>---------------------</td>
<td>-----------------</td>
<td>---------------</td>
</tr>
<tr>
<td>Mean ($)</td>
<td>0.1199</td>
<td>0.1542</td>
<td>0.1403</td>
<td>0.1262</td>
<td>0.1635</td>
<td>0.1378</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0208</td>
<td>0.0254</td>
<td>0.0282</td>
<td>0.0145</td>
<td>0.0159</td>
<td>0.0199</td>
</tr>
<tr>
<td>No. of Changes</td>
<td>39</td>
<td>36</td>
<td>38</td>
<td>8</td>
<td>12</td>
<td>28</td>
</tr>
<tr>
<td>Average No. of Weeks between Changes</td>
<td>2.13</td>
<td>2.31</td>
<td>2.18</td>
<td>10.37</td>
<td>6.92</td>
<td>2.96</td>
</tr>
<tr>
<td>Average Absolute Change ($)</td>
<td>0.0331</td>
<td>0.0378</td>
<td>0.0453</td>
<td>0.0097</td>
<td>0.0090</td>
<td>0.0208</td>
</tr>
<tr>
<td>Average Absolute Change (%)</td>
<td>30.72</td>
<td>27.26</td>
<td>35.89</td>
<td>7.72</td>
<td>5.65</td>
<td>15.43</td>
</tr>
<tr>
<td>Maximum Absolute Change ($)</td>
<td>0.0583</td>
<td>0.0675</td>
<td>0.0858</td>
<td>0.0250</td>
<td>0.0225</td>
<td>0.0544</td>
</tr>
<tr>
<td>Maximum Absolute Change (%)</td>
<td>53.47</td>
<td>59.78</td>
<td>69.95</td>
<td>20.17</td>
<td>14.03</td>
<td>41.73</td>
</tr>
<tr>
<td>Minimum Absolute Change ($)</td>
<td>0.0833</td>
<td>0.0167</td>
<td>0.0217</td>
<td>0.0038</td>
<td>0.0013</td>
<td>0.0063</td>
</tr>
<tr>
<td>Minimum Absolute Change (%)</td>
<td>5.75</td>
<td>9.58</td>
<td>18.36</td>
<td>3.30</td>
<td>0.81</td>
<td>3.88</td>
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</table>
Table 6. Summary of the impulse response analysis: original data

<table>
<thead>
<tr>
<th>Channel</th>
<th>Rigid</th>
<th>Tends toward rigid</th>
<th>Tends toward flexible</th>
<th>Flexible</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spot-to-Wholesale</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Wholesale-to-Retail</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Spot-to-Retail</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>7</td>
</tr>
</tbody>
</table>

Note: see the text for the definitions of the terms “rigid/flexible” and “tends towards rigid/flexible.”

Table 7. Summary of the impulse response analysis: moving averaged data

<table>
<thead>
<tr>
<th>Channel</th>
<th>Rigid</th>
<th>Tends toward rigid</th>
<th>Tends toward flexible</th>
<th>Flexible</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spot-to-Wholesale</td>
<td>5</td>
<td>3</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Wholesale-to-Retail</td>
<td>0</td>
<td>2</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Spot-to-Retail</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>8</td>
</tr>
</tbody>
</table>
Chart 1. Schematic Description of the Florida Frozen Concentrated Orange Juice Market

Note: This chart is a simplified description of the organizational structure of the Florida orange juice market. Orange juice growers sell the fruit to orange juice manufacturers/processors who convert the oranges into frozen concentrate. There are two types of processors: one group of processors are privately owned and produce orange juice for private label. The other group of processors are owned by national orange juice manufacturers like Tropicana and Minute Maid, and they produce nationally branded products. The manufacturers/processors package and sell the concentrated juice to retailers, either in its frozen form or reconstituted from concentrate and packaged as refrigerated juice. Oranges are also sold for other uses such as for preparing freshly-squeezed juice, for table use, for producing food additives, and so forth through other channels of distribution. These additional uses and their associated channels are not shown on the chart since in this paper we only study the market for frozen concentrated and refrigerated (reconstituted from frozen concentrated) orange juice. See Ward and Kilmer (1989) for details.
Chart 2. Cost and Price Series of Frozen Heritage House, 12oz (dollars/oz)

<table>
<thead>
<tr>
<th>Week</th>
<th>Spot Price</th>
<th>Wholesale Price</th>
<th>Retail Price</th>
</tr>
</thead>
</table>

Note: The chart shows the weekly variation of Spot Price, Wholesale Price, and Retail Price for Frozen Heritage House, 12oz, in dollars per ounce over a period from Week 0 to Week 88.