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Prices Rise Faster than They Fall

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Abstract

When the cost of an important input rises output prices tend to respond faster than when costs decline. This tendency is found in more than 2 of every 3 markets examined. It is found as frequently in producer good markets as in consumer good markets. In both kinds of markets the asymmetric response to cost shocks is substantial and durable. On average the immediate response to a positive cost shock is at least twice the response to a negative shock, and that difference is sustained for at least 5 to 8 months. Unlike past studies, which documented similar asymmetries in selected markets (gasoline, agricultural products, etc.), this one uses large samples of diverse products: 77 consumer and 165 producer goods. Accordingly the results suggest a gap in an essential part of economic theory. As a start on filling this gap the study finds no asymmetry in the response of an individual decision maker (a supermarket chain) to its costs, but it finds above average asymmetry where a cost shock is filtered through a fragmented wholesale distribution system. It also finds a negative correlation between the degree of asymmetry and input price volatility and no correlation with proxies for inventory costs, asymmetric menu costs of price changes and imperfect competition

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When business people are similarly questioned their answers are more varied. Alan Blinder and his associates (1994, 1997) asked them "How much time normally elapses after a significant increase (decrease) in cost before you raise (decrease) your prices?" Their answers implied symmetric lags in price adjustment. However, Blinder also asked why there was any lag at all. The most popular answer was a fear of getting out of line with competitors by being the first to raise prices after costs increased. This would seem to imply faster response to cost decreases, since early response in this case would confer competitive advantage. A survey of New Zealand businesses (Buckle and Carlson, 1996) yields the more traditional "prices rise faster" asymmetry.[2] Thus the business peoples' answers appear to cover every logical possibility.

Economists would probably side with (the central tendency of) the business people. Our theory suggests no pervasive tendency for prices to respond faster to one kind of cost change than another. In the paradigmatic price theory we teach, input price increases or decreases move marginal costs and then prices up or down symmetrically and reversibly. Usually we embellish these comparative statics results with adjustment cost or search cost stories to motivate lags in response. But the embellished theory suggests no general reason for these costs to induce asymmetric lags.

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[2] The survey used by Buckle and Carlson does not ask directly about speed of response as Blinder's did. Instead, it asks separately: whether prices were raised or lowered and, among other things whether costs increased or decreased in a specific quarter. They find that price and cost increases are paired more frequently in the same quarter than price and cost decrease.

Economists have a well-honed skepticism of lay beliefs about how markets work when those beliefs conflict with our theory. However, the fragmentary facts do not support that skepticism in this case. Studies involving gasoline (Borenstein, 1997; Karrenbrock, 1991), various agricultural products (Karrenbrock, 1991) and bank deposit rates (Jackson, 1997; Neumark and Sharpe, 1992) all find that retail prices respond more quickly to input price increases than decreases.[3] If that finding was shown to be general and not just limited to a few case studies it would point to a serious gap in a fundamental area of economic theory.

My aim here is precisely to generalize, or at least broaden dramatically the evidence on how prices respond to cost changes. I examine literally hundreds of markets involving both producer and consumer goods to see if there is any central tendency in the speed with which output prices respond to cost changes. The title summarizes the main result: the person-in-the-street is right and we are wrong.

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[3] For deposit rates the finding is that they respond more promptly to falling money market rates than to rising market rates.

The paper is unrepentantly descriptive. I try to develop some facts that our theory of markets will have to subsume rather than test some specific hypothesis. Accordingly the next two sections describe the data I use and what they tell us about the central question of how fast prices respond to costs. Here, I distinguish producer from consumer markets in part because most of the case studies have looked for asymmetries in consumer markets and because that is where most lay opinion undoubtedly expects to find them. Indeed, Borenstein showed that the main asymmetry in gasoline prices occurs between wholesale and retail gasoline prices, not between crude oil and the refined product. However, I find about as much asymmetry in producer goods as in consumer goods.

I also examine the response of one decision maker – a large supermarket chain in Chicago – to its wholesale costs and find no asymmetry at all there. Taken together then the findings suggest that asymmetry is a result of market interactions rather than some widespread decision rule.

The penultimate section fishes for some correlates of asymmetry. For example, I examine the role of traditional proxies for "market power" (concentration, numbers). The notion that some weakness of competition underlies price asymmetries is commonly mentioned in the case studies (Karrenbrock, 1991) and sometimes finds support (Jackson, 1997; Neumark and Sharpe, 1992). This notion also gives the issue occasional policy relevance and would surely provide a starting point for much theoretical work on the subject. However, I find that attributing asymmetries to imperfect competition is unlikely to be rewarding. There are other negative findings – for example, on the roles of inventories and inflation-related asymmetric 'menu costs' of price change. And there are some positive findings – on input price volatility and the structure of intermediary markets.

The conclusion tries to focus the obvious challenge posed by my results to our theory of markets.

II. Data

I analyze three samples of data. Each contains numerous time series of output prices matched to input prices. Two of the samples come from publicly available Bureau of Labor Statistics (BLS) data; the third is from a University of Chicago Graduate School of Business database supplied by a local supermarket chain.

I use all the data to answer questions like: if costs go up today how long does it take for prices to go up and by how much do prices rise? I use coefficients from regressions explaining price changes with current and past cost changes to answer this question. To implement this I have to link some price measure with a cost measure within a relevant market. In the typical case study, comparatively rich data on one product are analyzed intensively. For example, Borenstein analyzes weekly, city-level retail and wholesale gasoline prices. This level of disaggregation is appropriate if the price adjustment is completed in a few weeks and markets are local. My goal of examining many markets at once requires a different approach. It would be impracticable to investigate the appropriate time-space aggregation for each of hundreds of products let alone hope to find corresponding data. So I use the cruder data – monthly national averages – that are available for many goods and focus on the central tendencies emerging from analysis of the sample rather than on results for specific goods. I presume that any errors arising from the crudeness of the data are not systematic and become small by averaging.

Here I describe the main features of the three samples leaving details to an appendix.

1. The Producer Price Sample

The BLS Producer Price Index (PPI) is an aggregate of over 1500 components. Each component is a monthly index of the national average price for some producer good. The price is for the first transaction that occurs after production of good. This is a transaction between firms rather than between businesses and consumers. I use the fact that some of these producer goods are inputs in the production of others to study the transmission of cost changes within the producer goods sector.

One way of doing this would be to aggregate some appropriate PPIs (e.g., PPIs for flour, sugar, energy) into a single input cost index to "explain" another (the bread PPI). However, for tractability (and comparability with the skimpy case study literature), I do something simpler: I analyze only those outputs where a single input accounts for a significant fraction (over .2) of the output's value. Then I use the PPI for that input to explain the output PPI. One cost of this simplicity is an unrepresentative sample. It tends to be skewed toward outputs produced with simple technologies in which the input is heated, crushed, bent, pummeled, butchered, etc. By construction the sample excludes high value-added products.

The Appendix gives a detailed description of how the sample was put together and how I resolved data problems. Briefly, I began with the input-output "use" tables which give each (approximate 3 or 4 digit) industry's purchases from every other. Pairs where the cost share (industry *i's* purchases from *j* / *i's* shipments) exceeded .2 were pursued further using the more detailed data in the Census of Manufactures. I used the Census to refine the matches and the cost shares to the least aggregated level permitted by the data. In some cases I consulted industry sources to identify appropriate matches. Finally, I used a linkage between the Standard Industrial Classification (SIC) and PPI commodity codes provided to me by the BLS to identify the specific PPI indexes to be matched. This process resulted in a sample of 165 input-output pairs with sufficient data for my purposes.

Generally the sample period is 1978 – 1996. The starting point coincides with the BLS' reform of the PPI to more accurately measure transaction prices. While double-digit inflation characterizes the early part of this period around 85 percent of the sample period is from the subsequent mild inflation regime.[4]

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[4] The double-digit PPI inflation broke suddenly in the Spring of 1981. Subsequently PPI inflation has averaged under 2 percent per year.

Table 1 provides an industrial distribution of the inputs and outputs and gives some relevant summary statistics. The concentration in food and metal products (over half the outputs) is evident. However, most of 'low-tech' manufacturing (roughly, 2 digit SICs < 35) is represented. There is enough price volatility in this sample to permit extracting any asymmetries from the data: input and output prices change in most months, and non-trivial changes in both directions are common.

2. Consumer Price Sample

Like the PPI, the BLS consumer price index (CPI) is an aggregate of numerous component indexes. Each measures the retail price of a specific good or service. Since each of the goods in the CPI has in principle some counterpart in the PPI, I constructed a sample in which these counterparts were matched. The goal in doing this is to estimate how retail markets convert cost shocks specific to them – changes in the producer prices of finished goods – into price changes faced by consumers.[5] The appendix gives the details of how CPI and PPI indexes were matched and how I resolved related problems. Conceptual differences in the construction of the two indexes preclude a direct matching; there is no "retail widgets" price index that is the precise counterpart of a "manufactured widgets" price index. Substantively, the least aggregated

[5] I did not pursue the chain of production further to ask how primary product price changes (e.g., crude oil, cattle) ultimately feed into consumer good prices (retail gasoline, meat). This would have been feasible for only a handful of consumer products where the primary product is a sufficiently important cost component. Nor did I pursue the chain of distribution. Systematic data on prices paid by retailers to wholesalers is unavailable. So the PPI is, strictly speaking, a retailer input cost index only when retailers buy directly from the manufacturer.

CPI indexes tend to be more aggregated than the corresponding PPI indexes. This makes the consumer price sample smaller than the producer price sample. Also, I usually had to aggregate to obtain a match with the corresponding CPI index. Neither the items nor the weights (factory shipments) used in the aggregation necessarily correspond to those in the CPI index. And, I dropped some CPI indexes because the degree of aggregation seemed too great for the purpose at hand.[6]

I matched 77 CPI index with PPI counterparts. Table 2 gives some salient characteristics of this sample. It is heavily weighted toward food items, mainly because these are numerically overrepresented among the detailed CPI indexes. Nevertheless the sample items account for around half of total consumer spending on physical goods.[7] Like the producer price sample, there is no shortage of "price action" in this sample. For a typical item, both producer and consumer price indexes change about 9 months in every 10, and there is considerable volatility. The volatility of the typical sample item's producer price is not too different from the stock market. At this level of disaggregation, neither the CPIs nor PPIs look anything like the smoothly rising aggregate series familiar to most of us.

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[6] Examples would include "sewing materials, notions, luggage" or "lawn equipment, power tools and other hardware."

[7] A list of the sample items and corresponding PPI indexes is available or request.

3. Supermarket Prices

I have data on the retail and wholesale prices of individual items at the universal product code (UPC) level sold by the second largest supermarket chain in the Chicago area. The items are from a selection of packaged good (i.e. not fresh produce, meat, etc.) categories accounting for about a third of total store sales, and the wholesale price is an average of recent transaction prices rather than the last transaction prices. Retail prices for a UPC can vary across the stores in the chain. For most UPC, store pairs I have retail and wholesale prices for 65 "months" (4 week periods) from September 1989 through September 1994.

As usual, the appendix provides detail on the sampling procedure and my treatment of specific problems, such as the averaging in the wholesale price data. Generally, I tried to select the 5 largest selling UPCs from each category and obtain their prices from a stratified random sample of 4 stores. I obtained usable data from 24 product categories (listed in the appendix), so the maximum number of "store, UPC" pairs was 480 (5 UPCs x 4 stores x 24 categories). Of these, 357 appear in my sample. One reason for dropping a UPC was paucity of wholesale price changes, so the sample is biased toward items with frequent price changes.

I formed two subsamples from these data. One uses the store, UPC pair as the primary unit of analysis. Here we answer "how does the price of a specific item – an 18 oz box of Kellogg's Corn Flakes – at a specific location responds to a change in that item's wholesale price?" Because price changes across the chain's stores (and, to a lesser extent, price changes across UPCs) are not independent, there are fewer than 357 "real" degrees of freedom available to answer such questions. Accordingly, I will focus on category wide averages in the analysis of this sample.

The second sampling of these data uses the product category as the unit of analysis. Here the question is: how does the average price of cereal in the Chicago area respond to a change in average wholesale prices? For this purpose, I first combine the wholesale and retail prices of each UPC at each store into price indexes (UPC sample mean = 100). Then I average these indexes across all the UPCs in a category to get the category-average index. So the category index gives equal weight to each UPC.

The category-average sample excludes categories with only a single UPC and categories where the averaging process leaves too few (non de minimus) wholesale price changes for my purposes. Sixteen categories remain in this sample.

Table 3 summarizes some salient characteristics of the UPC store, and category average samples. The overwhelming impression is one of considerable price volatility. Standard deviations at the UPC level are two to four times larger than the CPI or PPI indexes in Tables 1 and 2. Averaging across the UPCs of course reduces price volatility, but it remains larger than the CPI or PPI indexes. The category average indexes change about as frequently as the CPI and PPI indexes. But increases and decreases seem a bit more equally represented in the supermarket data.

III. Empirical Procedure

For each input-output price pair in each of the three price samples I fit two time series models. The first is a simple distribution lag (DL) of the general form.

$$\text{(1) Change in output price}_t = \sum_{i=0}^{K} b_{t-i} \cdot (\text{change input price})_{t-i}$$

$$+ \sum_{i=0}^{K} c_{t-i} \cdot (D \cdot \text{change input price})_{t-i}$$

$$+ \text{ other variables}$$

where D = +1 if change input price > 0, 0 otherwise.

Here current and lagged changes in the price of some input are allowed to affect an output price asymmetrically and with a lag. Since (1) is, in principle, a reduced form, it allows for "other (supply and demand shifter) variables" in addition to the supply side shock captured by the input price change.

The DL model has the virtue of simplicity and of providing a straightforward description of price adjustment. However, my sketchy treatment of the "other variables" (see below) may mean that the DL under - utilizes the available price data. For example, if output price responds gradually to (unmeasured) demand shocks as well as to (measured) cost shocks this would show up in an autoregressive process in the output price changes. Therefore, to allow for a more flexible adjustment process I also estimate vector autoregression (VAR) models of the general form:

(2) (change in output price)$_t$ = same terms as in (1) + $\sum_{i=1}^{N} e_{t-i} \cdot$ (change in output price)$_{t-i}$ + f · [level of output price – equilibrium level]$_{t-i.}$

The additional terms in (2) allow for some mixture of an autoregressive process and an 'error-correction' process. The autoregressive process is represented by the lagged output price change terms. The coefficients of these terms would be positive (negative) if there is slow (rapid) entry or exit in response to unmeasured shocks.

The error correction term (the last term in (2)) also allows for entry/exit. If prices have drifted away from equilibrium values because of incomplete adaptation to past shocks then current supply changes should move them back toward equilibrium. Accordingly, I expect f to be negative. Operationally, I set the error correction term, with one exception, equal to the lagged value of (log output price – log input price). This presumes a fixed equilibrium markup of input prices over the sample period for each good. The exception is the UPC sample of supermarket prices. Here I use the log of an index of average retail price of other UPCs in the same product category, rather than the UPC's wholesale price, as the proxy for equilibrium price. In preliminary work I found that for an individual item, like Kellogg's Corn Flakes, the fact that its price was out-of-line with the price of other cereals was more germane than its own markup.

The VAR model could be further complicated by allowing for asymmetries in the auto-regressive and error correction processes. But this would begin taxing comprehension and degrees of freedom. So I restrict all the asymmetries in the VAR model to those arising from response to the measured cost shocks.

My goal in applying (1) and (2) to the data is to answer a general question: how frequently do prices respond asymmetrically to cost shocks? Accordingly, I eschew any attempt to custom-tailor these models to the circumstances of individual markets. Instead I fit the same model – the same lag structure and the same list of other variables - to each input-output pair within any of price sample.

To find this common model, I first tried to determine how many lags were required to more or less fully describe the price adjustment process within any price sample. I did this by estimating preliminary sets of regressions without asymmetries. Each set imposed the same lag length (the K or N) on all the price pairs in a group beginning with $K = 0$ or $N = 1$. I then increased the values of K or N progressively until marginal explanatory power seemed exhausted. The resulting value of K or N was then imposed on all estimates of (1) or (2) for the sample.[8]

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[8] I determined N and K in the VAR model iteratively. I began with the K that worked for the distributed lag and then varied N as described. Once N was determined, I allowed K to vary further, etc.

To elaborate by example, subsequent results from the distributed lag model for the 77 CPI indexes come from 77 estimates of (1) each with $K = 4$. I chose $K = 4$ because the number of significant coefficients obtained by adding more lag terms to the 77 regressions was only about what one would expect by chance.[9] Undoubtedly, $K = 4$ is too big for some markets and too small for others. But this is not systematically concealing information, and, for my purpose, seems preferable to conducting 77 specification searches.

For the VAR model, a similar procedure led me to set $K = 5$ and $N = 4$ (i.e. estimate (2) with 6 current and lagged input price changes and 4 autoreggressive terms) for each of the 77 CPI regressions. I repeated this algorithm on the PPI and supermarket price samples to obtain the K and N values appropriate for each of these samples.

A similar pragmatism drove my choice of the "other variables" in (1) and (2). These should include cost shocks other than the specific input price changes already included plus demand shifters. It was impracticable to customize a list of such variables for each of the hundreds of markets analyzed. Accordingly, I looked only for some broad aggregate measures that could be added to all of the regressions in a group. That search led to inclusion of the current and 3 lagged changes in the log of:

1. the PPI for all finished goods less food and energy

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9 If 77 regression coefficients are drawn from a random process with a zero mean, there should be around 10 with $|t|$ ratios > 1.5, 4 with $|t|$ > 2.0, etc.

and

2. the Industrial Production Index in all of the PPI regressions,

and

3. the CPI for all items less food and energy in all of the CPI regressions.

These summarize the impact of economy-wide nominal demand and/or cost changes, and a sufficient number of their coefficients were significant to warrant inclusion in the regressions.[10] However, they are included mainly for completeness: No essential result in the paper would change if they were dropped.

Finally, each regression includes month dummies to de-seasonalize the input and output prices.[11]

I use the regression results to answer two questions:

1. How common is asymmetric price response to costs?

2. How large is any such asymmetry?

The unit of observation here is the input-output pair as described by time series regressions like (1) and (2). For the DL model (equation (1)) the answers come directly from the coefficients on the input price changes. In that model, the cumulative response after k months to an input price decrease in month t is:

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[10] I used the "less food and energy" versions of the aggregate price indexes to reduce potential collinearity and double-counting. Food and energy items are prominent among the inputs and outputs in both the CPI and PPI samples.

[11] These do not appear in the supermarket price regressions. Preliminary work showed essentially no seasonal price patterns in that sample; it also has the fewest degrees of freedom per regression.

$$(3)\ \sum_{i=0}^{k} b_{t-i},$$

And the cumulative response to a price increase is

$$(4)\ \sum_{i=0}^{k} (b_{t-i} + c_{t-i}).$$

So, if the difference between these, or

$$(5)\ \sum c_{t-i}$$

is positive, there is a positive asymmetry: output prices respond more fully to a positive cost shock over the k month period. And (5) gives the magnitude of the asymmetry. For the VAR model (equation (2)), it is necessary to take account of the feedback between output price changes today and tomorrow (via the auto-regressive and error-correction terms). Accordingly, for each input-output pair in each sample I used the VAR regression coefficients to estimate cumulative responses to +1 and −1 input price shocks respectively.[12] Then I estimated the asymmetry after k months as

$$(6)\ \sum_{t=0}^{k} \Delta\hat{P}^{+}_{t+i} - \sum_{t=0}^{k} \Delta\hat{P}^{-}_{t+i}$$

where, the $\Delta\hat{P}$ = estimated response of output price in month $t+i$ to a + or -1 change in the input price in month t.

[12] However, I constrained the error-correction coefficient to zero if its estimated value was positive. A positive coefficient implies implausibly that prices do not converge to equilbruim. Empirically, imposing the constraint makes no substantive difference: 1) positive error-correction coefficients occurred in less than 10 percent of the regressions in any price sample; 2) when I removed the constraint none of the main results derived from the VAR estimates changed; 3) as elaborated later, these results are, in any case, essentially the same whether the DL or VAR is used.

IV. Estimates of Asymmetric Price Response

A. Producer Price Sample

Table 4 summarizes the results of estimating the VAR model (equation (2)) on 165 producer goods for which a single input accounts for at least 20 per cent of the good's value. Panel A gives estimates of the average values of each of the two terms in (6) and Panel B focuses on the difference between these two. (Results from the distributed lag model are essentially the same as those in Table 4). The entries on panel A, line 1 mean that for the average good in the sample a one percent input price increase in $t=0$ leads to a .235 percent output price increase in the same month, and after 8 more months the output price has risen a total of .505 percent.[13]

The results in panel B point to a single conclusion: positive asymmetry is a fact-of-life in industrial markets. It is pervasive – over 2/3 of the sample markets exhibit positive asymmetry in $t=0$. It is large – the $t=0$ response is nearly twice as great when input prices rises as when they fall. And the phenomenon lingers – only at $t=8$ is there even faint evidence of a narrowing in the gap between responses to input price increases and decreases. That gap ought to disappear entirely – else a negative cost shock would permanently raise price-cost margins – but it is not doing so within the period where I can find measurable responses to the cost shock.

[13] To put this number in perspective, note that the average input cost share in this sample is .43 which would be the expected average response under, say, Cobb-Douglas or Leontieff production.

The preceding results all hold when the sample is carved up by input cost share[14] and by industry. In the latter case, the individual estimates in panel B. III are often insignificant due to the small size of the subsamples. But the noteworthy feature here is the overwhelming number of positive point estimates (29 of 32). Clearly the phenomenon of positive asymmetry is not confined to only a few kinds of industrial products.

B. Consumer Price Index Sample

In Table 5 I repeat the preceding analysis for the sample of 77 consumer goods for which I can match a CPI index to a PPI 'input' index. The results are remarkable more for their similarity to producer goods markets than for any differences. Once again we see that an overwhelming majority of these consumer markets exhibits positive asymmetry. The size, persistence and pervasiveness of the positive asymmetries here essentially mirror those in producer good markets. If anything these characteristics are a bit stronger for consumer goods. But no relevant test would reject the equality of the asymmetries in consumer and producer markets at similar stages of the adjustment process.

C. Supermarket Prices

There is a sharp contrast between the preceding results and those for prices at a specific supermarket chain as summarized in Table 6. Here the unit of observation is the product category, and the table gives summary statistics across the sample categories. These are shown for two distinct levels

[14] None of the differences between lines b) and c) in panel B are significant.

of aggregation. In the 'UPC sample' equations (1) and (2) are estimated for individual UPCs at a specific stores. Then I use the regression coefficients to generate estimates of the cumulative response to wholesale price changes for each UPC/store pair. Finally, I average these estimates over all UPC/store pairs in a product category. That average answers a question like 'how quickly does a change in the wholesale price of a typical brand of cereal get reflected in the retail price of that brand at a specific store?' The 'product average sample' answers 'how does the average price of cereal at this chain respond to changes in the chain's average wholesale price of cereal?' Here I run only 1 regression on each product category. It uses indexes of average prices across all the UPC/store pairs in that category. However, as the table shows, the degree of aggregation makes no difference in practice for the behavior of interest here.

The most prominent feature of Table 6 is the absence of any systematic asymmetry in Panel B. The plethora of insignificant differences from symmetry speaks with one voice in this respect.

The results in Table 6 seem to deepen the conundrum about the preceding results. They suggest that asymmetry at the market level is not produced by some simple aggregation of individual decisions to respond asymmetrically. Instead these results suggest that some subtlety of the interaction of these individual decisions produces the asymmetry. This would, of course, hardly be the first time in economics that the distinction between individual and market behavior was important.

There are some other notable differences between the supermarket chain's price response and the market-level responses studied earlier. These may either reinforce the last point or be ground for caution about the results. The one difference visible in Tables 5 and 6 is the much faster adjustment at the firm than market level. A one percent wholesale price change ultimately leads to roughly the same retail price response in both - - around .4 to .5 percent. But at the firm all (or even more) of the (measurable) response occurs in the month of the wholesale change while the market adjustment is spread over six months. One source of this difference – hinted at by the mildly saw-toothed pattern of the cumulative responses in Table 6 but not shown explicitly – is the greater tendency toward mean reversion the in firm's response. This is consistent with the competitive constraints on the firm.[15]

Those constraints, in turn, suggest a different response by the firm to market-wide than to idiosyncratic shocks. (The mean reversion suggests that competition quickly offsets the latter.) And there does appear to be a large idiosyncratic component in the firm data.

Table 7 illustrates this. It compares the behavior of product category price indexes at the supermarket chain to matched CPIS and PPIs. The

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[15] Specifically, the estimated auto-regressive and error-correction components of equation (2) are mostly negative in both the supermarket and CPI samples, but they are only important in describing the firm level data. To illustrate, for the average product category in the supermarket sample, 60 percent of a unit change of the retail price index is offset after a month.

The size of the offset conveys an impression of something like 'price-taking' behavior by the firm: when the firm gets 'out-of-line' with the market most of this discrepancy is erased in a month.

matches are not perfect – in most cases the closest corresponding CPI or PPI was a bit more aggregated ('canned seafood') than the supermarket category ('tuna'). But this does not obscure the message in the table: the national price indexes average out a lot of firm specific or local 'noise.' This is most clear in panel B, which shows the standard deviation of monthly price changes. At the supermarket these are 3 to 5 times as large as corresponding PPIs or CPIs. The other panels focus on the long-run trends in these data. The supermarket and national prices move broadly together over the 5 year sample. Panel C shows that, on average, trends in a CPI or PPI are matched essentially point-for-point by the companion supermarket index. Panel A shows that the mean changes are about equal. But even at this long frequency the supermarket trends are much more variable (compare the standard deviations in Panel A).

This noise creates a substantial signal – extraction problem for the firm, if it wants to respond differently to the signal in the wholesale price data than the noise. We do not know how the firm solves this problem, so Table 6 may show mainly the firm's response to the noise.[16]

V. Exploratory Analyses of Price Asymmetries

The obvious question raised by the preceding section is: why are asymmetries so pervasive in real-world markets? Unfortunately, I have no

[16] Unlike the mean-reverting retail prices, there is no obvious time series process characterizing the wholesale prices. And the zero order correlation of monthly wholesale price changes with the change in the matched PPI averages close to zero. Attempts to substitute the PPI change for the firm's wholesale price change in estimates of equations (1) or (2) proved unrewarding.

answer. Instead, I investigate a more limited question: are there obvious regularities in the asymmetries? I do this by regressing the degree of asymmetry on a list of readily available market characteristics. The hope here is that the larger theoretical question will at least come into better focus. For example, industrial organization specialists (and non-economists) would be drawn to theories based on imperfect competition. So I include conventional market structure measures - concentration and numbers - in the analysis. Macroeconomists have focused on 'menu-cost' explanations of price rigidities generally (Sheshinski and Weiss, 1993) and inflation induced asymmetries in menu costs in particular. For example, in Ball and Mankiw (1994), secular inflation, by reducing real prices, allows firms to avoid the menu-cost of prompt response to a negative cost shock. Accordingly, I analyze measures of input price behavior designed to capture the importance of asymmetric menu-costs.

Table 8 describes the independent variables used in the analysis. The four succeeding tables (9 through 12) summarize the results. The independent variables fall into two broad categories: those describing the behavior of input prices and those describing the structure of the input or output producing industries. In the case of consumer goods, I also include some characteristics of the wholesale intermediaries between the producers of the 'inputs' (the goods) and the producers of outputs (the retailers). Input price behavior variables include the input's cost share, its price volatility and two variables related to menu-costs: the drift of input prices and the differential persistence of positive v. negative input cost changes. Menu-cost stories would imply a positive correlation between both variables and the degree of asymmetry. If input prices are rising and input price increases tend to be more permanent than decreases, fast response to input price decreases could waste menu-costs.

The industry variables include standard measures of competitive structure (numbers, HHI), market size, production technology (assets/sales) and inventory holdings. The latter are proxies for storage costs which should affect the speed (but, not in any obvious way, the asymmetry) of response to cost shocks. In addition we include measures of the geographic concentration of suppliers and buyers. The motive here is to see whether propinquity affects the speed of price propagation. Here too, even if there is an effect, there is no reason to expect it to be asymmetric.

Given the theoretical vacuum, I let the data speak by first using all the available independent variables and then winnowing the list to those variables which show some 'promise' in the first regression. This two step process is summarized for the producer goods sample in Tables 9 and 10. The former table shows two alternative measures of asymmetry: one (DL) comes from application of the distributed lag model in equation (1); the other (VAR) uses the vector auto-regression model in equation (2). The asymmetries are measured during the month of the input cost shock and after 2 and 8 more months of adaptation to it.[17] Table 9 shows results for OLS and weighted least

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[17] I chose these lags to keep the detail manageable and to keep the information overlap in the regressions reasonably small. Since the asymmetry measure is cumulative, there is a

squares (WLS) regressions. The WLS regressions use information on the variance of the asymmetry estimates produced by the DL or VAR model. That information is valuable: plots of the OLS residuals revealed obvious heteroscedasticity in the residuals, and it is was entirely cured by giving greater weight to observations with tighter distributions around the asymmetry estimate. Finally, I enter logs of variables with substantially right-skewed distributions.

The letters in Table 9 summarize the sign and statistical significance of the coefficients of all the listed variables (blanks mean "$|t|<1$"). No variable is resoundingly significant in every specification. So some judgment was needed for the refinement reflected in Table 10. In weeding out variables, I over-weighted the WLS results in Table 9, because the data so clearly reject the appropriateness of OLS. And Table 10 shows only the WLS results. Also, as is evident in Table 9, DL and VAR results are essentially the same so only the latter appear in Table 10.

Two positive results emerge from this two-stage fishing expedition: 1) less input volatility is associated with more asymmetry, and 2) the structure of output markets 'matters,' but in a way that resists easy labeling. The negative impact of input price volatility seems the more robust of the two. It

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positive correlation across the various lags. However, for the three lags in Tables 9 and 10, these correlations (for the VAR measure) are

	month 2	month 8
month 0	.22	.26
month 2		.55

So the various lags are hardly mirror images of each other.

shows up in every specification in Table 10. Both effects seem weaker when input cost shares are smaller.

Does less competition produce more asymmetry? The answers from Table 10 are conflicting, even contradictory. Two conventional proxies for competition – numbers and concentration – have opposing effects. Fewer competitors is associated with more asymmetry, but more concentrated markets produce less asymmetry. Empirically, of course, these proxies are not independent: markets with fewer competitors tend also to be more concentrated. Accordingly, I took account of that empirical relation to estimate a total effect of 'increased competition.' I did this for the two specifications where the effects of the two market structure variables are greatest (the 8 month lag for the full and 'cost > .4' samples). One calculation (for the full sample) implied that more competition reduced asymmetry; the other implied the opposite.[18]

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[18]Let

A = degree of asymmetry
N = number of firms (logs)
H = HHI measure of concentration (logs).

We want, for example, to estimate,

$\frac{dA}{dN}$, taking into account that more firms generally implies lower H. This would be:

$$\frac{dA}{dN} = \frac{\partial A}{\partial N} + \frac{\partial A}{\partial H} \cdot \frac{dH}{dN},$$

where the partial derivatives are the coefficients in Table 10 and

$\frac{dH}{dN}$ can be approximated by the slope obtained by regressing H on N. Similarly, we

If the results do not cry out for imperfect competition stories, neither do they provide much encouragement for menu-cost or inventory models. None of the proxies for these latter two are consistently important.

Tables 11 and 12 contain a trimmed version of the same two step analysis, for consumer goods. (Only the VAR results are shown, because the DL results were essentially the same). The input price here is an index of prices charged by manufacturers while the output price measures retailer prices. However, manufacturers often sell to intermediaries rather than directly to retailers. So Tables 11 and 12 include some characteristics of the wholesalers who handle the good.

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can estimate

$$\frac{dA}{dH} = \frac{\partial A}{\partial H} + \frac{\partial A}{\partial N} \cdot \frac{dN}{dH}.$$

Estimates of these total derivatives imply a significant negative correlation between competition and asymmetry in the full sample and a significant positive correlation in the high-input-cost subsample.

One notable result of the consumer good analysis is the negative effect of input price volatility. This mirrors even in rough magnitude the result for producer good markets. Taken together, the two results suggest that the mysterious good 'delayed response to input price reductions' at least obeys the law of demand. The 'price' of failing to increase supply when input prices fall is the loss of the extra margin on incremental sales. This price is greater – and the output response is apparently less restrained - when input prices are more volatile.[19],[20] Moreover, the effect is empirically important. For example, suppose price volatility rose by a standard deviation. The regressions imply that the 2 month asymmetry measure would then fall by about half in both the producer and consumer good sample.

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[19] The discussion here refers to the size of price decreases rather than overall volatility. However, empirically the two are basically indistinguishable. The correlations between the logs of the standard deviation of prices and the mean absolute price decrease are .95 and .98 for the producer and consumer good samples respectively.

[20] For example, consider a price taker with marginal cost = X; X = Output produced by a single variable input. If the input price falls by $100 \cdot \delta$ percent, the usual story would have X go from p (= price) to $P/(1-\delta)$, and the profits from the incremental output would be:

$$\frac{(P\delta)^2}{2(1-\delta)}.$$

If instead the firm increased output by only a fraction, k, of the difference between P and $P/(1-\delta)$, it would sacrifice profits of

$$\frac{[P\delta(1-k)]^2}{2(1-\delta)}.$$

For any k, this sacrifice is increasing in δ, the size of the input price reduction.

Table 12 also suggests that there is more asymmetry when the supply chain is more fragmented. When retailers obtain supplies directly from the manufacturer or from a few large wholesalers there is less asymmetry. The coefficients imply that half the mean 2 month asymmetry would be eliminated by a one standard deviation change toward less fragmentation in any one of the three wholesale market variables. So these effects are also important empirically as well as statistically.

Consumer markets, like producer good markets, provide little support for inventory or menu cost stories. In fact, the consumer price results seem perverse. For example, one might expect prices for goods with slim inventories to behave more like a text book spot market. However, low manufacturer inventories are associated with more rather than less asymmetry. Similarly, the negative coefficient of the (differential) persistence variable in Table 12 is opposite to that implied by a menu-cost explanation of asymmetry.

Finally, none of the retail market characteristics – their size, the density of stores, retailer inventories and margins – seem to have any connection to the degree of price asymmetry.

V. Summary and Conclusion

The odds are better than two to one that the price of a good will react faster to an increase in the price of an important input than to a decrease. This asymmetry is fairly labeled a 'stylized fact'. This fact poses a challenge to our theory of market behavior. That theory is surely a bedrock of economics. But the evidence in this paper suggests the theory is wrong, at least insofar as asymmetric response to costs is not its general case. It is surely an embarrassment that lay prejudice comes closer to the truth in this case than does our theory. Moreover, the theoretical problem is not trivial empirically. On average output prices immediately respond two to three times as much to an input cost increase as to a decrease. And the absolute size of the difference is maintained the whole period – 5 to 8 months – over which I am able to measure adaptation to cost shocks. Even if cost decreases do not increase profit margins permanently, full adjustment does take a good while.

The theoretical puzzle is unlikely to be solved by a roundup of the usual suspects. Price asymmetry is as characteristic of 'competitive' as 'oligopoly' market structures. It is found where the buyers are numerous and unsophisticated consumers as well as where they are large and presumably sophisticated industrial purchaser. Neither inventory holdings nor menu-costs seem a key ingredient in producing price asymmetries. The only clear regularity I found was that more volatile input prices are associated with less price asymmetry.

Perhaps the first path to a solution many economists will be drawn to would be 'adjustment costs,' since we regularly invoke these to rationalize lags in price response generally. For example, consider a good produced with inputs (the 'materials' studied here, 'labor' etc.) all purchased under 'at will' contracts. If the price of materials rises, inputs will have to be disemployed. This can be done quickly at low cost given the nature of the contract. However, if the price of materials falls, new inputs will need to be recruited. And there are costs to doing this quickly (search, price premia) which are absent when inputs are disemployed. This asymmetric adjustment cost story would be consistent with the kind of price asymmetry I find here.

My findings suggest some caveats and perhaps other paths for future research. I found no asymmetry when I examined the response of a single decision maker to its own costs. By contrast, I found above average asymmetry between factory and consumer prices when there were many small intermediaries between the factory and the retailer. This suggests that an explanation for asymmetry may require a fuller understanding of those vertical market linkages.

My research design was to focus on the easy cases – where a single input is a major cost component. This made it relatively easy to equate a 'cost shock' to the change in a single, often volatile, price series. But, at least for producer goods, my procedure results in a possibly unrepresentative sample of low tech, low value added items. And it leaves a large question for future research: do prices really respond asymmetrically to cost shocks generally? Or is the asymmetric response limited to one input price in cases where the input happens to be important?[22]

[22] The path to an answer is strewn with other difficult question: Is an input cost index the appropriate general analogue to the important single input for my sample? Or, are there many separate asymmetric responses to the prices of individual inputs? For many goods, the single most important input will be labor. Does the paucity of nominal wage reductions preclude answers to the preceding questions? etc.

Table 1. Producer Price Sample, 165 Input-Output Pairs. Summary

A. Industrial Distribution

Industry	**SICs (2-digit) Included**	**Percent of sample Outputs**	**Percent of sample Inputs**
Food, Agriculture	20, 01, 02	21.8%	28.5%
Textile, Leather	22, 23, 31	14.5	5.5
Crude Oil	13	--	3.6
Wood, Lumber	24	6.7	6.7
Paper	26	9.1	9.1
Chemicals	28	8.5	7.3
Petroleum, Rubber	29, 30	6.1	6.1
Stone	32	0.6	0.6
Steel	33, 34	17.0	17.0
Non-Ferrous metals	33, 34, 50	15.8	15.8
TOTAL		100	100

B. Sample Characteristics

	Mean	Q1	Q3
I. Frequency of Price Changes (percent of all months)			
A. Outputs			
1. Increases	43.8%	37.2%	52.0%
2. Decreases	34.1	23.9	45.4
B. Inputs			
1. Increases	47.2	41.8	52.5
2. Decreases	40.1	34.5	47.1
II. Standard Deviation of Monthly Price Changes (log x 100)			
A. Outputs	2.7	1.0	4.2
B. Inputs	4.1	1.5	5.9
III. Input Cost/Output Shipments	.429	.31	.50

Table 2. Consumer Price Sample. Summary

A. Commodity Categories	Number of Items in Sample	Percentage of all consumer spending on goods accounted for by items in: Sample	Category
Food	43	13.9%	35.6%
Alcoholic Beverage	4	3.5	3.5
Fuel	4	7.0	7.2
Apparel	6	3.9	12.6
Recreation	4	2.6	4.7
Other non-durables	4	2.1	10.0
Automotive	3	12.9	16.6
Household Durables	9	3.1	9.7
Total	77	49.0	100.0

B. Sample Characteristics	Mean	Q1	Q3
I. Frequency of Price Changes (percent of all months)			
A. Consumer prices			
1. Increases	58.5%	51.4%	66.4%
2. Decreases	37.5	28.4	46.8
B. Producer Prices			
1. Increases	54.0	47.8	61.6
2. Decreases	33.7	21.1	46.6
II. Standard Deviation of Monthly price changes (log x 100)			
A. Consumer prices	2.0	0.7	2.1
B. Producer prices	3.7	0.8	3.9

Table 3. Characteristics of Supermarket Price Samples

Characteristic	Sample					
	UPC, Store			Category Average		
	Mean	Q1	Q3	Mean	Q1	Q3
1. Number of categories	24			16		
2. UPC, store pairs per category	14.9	12	20	--		
3. Percentage of months with:						
a. increasing prices						
(1) at wholesale	34.3%	30.5%	38.0%	42.4%	39.5%	46.5%
(2) at retail	36.7	32.0	41.0	44.9	41.3	48.0
b. decreasing prices						
(1) at wholesale	30.9	24.0	36.0	40.6	35.0	46.7
(2) at retail	34.0	26.3	40.8	42.5	41.0	44.0
4. Standard Deviation, monthly changes in log prices (x100):						
a. wholesale	7.5	4.9	8.8	4.5	2.7	5.8
b. retail	8.3	5.8	9.8	4.4	3.1	6.1

Note: In 'UPC, store' sample the unit of observation is a single item (UPC) at a single store. There are up to 5 items and 4 stores per product category. The data shown for this sample are based on averages within product categories. For example, to obtain the 34.3% figure on line 3.a.1. I first obtain the percent of months with increasing wholesale prices for each store, UPC pair in a category. Then I average those to obtain a category average figure. Finally, I average the 24 category averages to obtain the 34.3% figure.

The 'category average' sample is based on one wholesale and one retail price index for each category. These indexes aggregate prices for all the store, UPC pairs within a category. Sample excludes categories with only one UPC.

Table 4. Asymmetries in Response of Producer Prices to Input Cost Changes

A. Mean Response to Input Cost Changes (full sample)[1]

	Sample Size	**Cumulative Response after Month:**			
		0	**2**	**4**	**8**
1. Input Cost Change = +1	165	.235	.371	.430	.505
2. Input Cost Change = -1	165	.127	.233	.270	.354

B. Asymmetries in Response to Unit Cost Changes

	Sample Size	**Cumulative Response after Month**			
		0	**2**	**4**	**8**
I. <u>Mean Asymmetry:</u>					
a) full sample	165	.108	.139	.160	.150
(= panel A. line 1 - line 2)					
• t-ratio		5.0	5.0	4.6	3.4
b) input cost share > .4	80	.147	.129	.130	.093
• t-ratio		4.8	3.2	2.4	1.6
c) input cost share ≤ .4	85	.071	.148	.189	.205
• t-ratio		2.4	3.9	4.4	3.0
II. <u>Share of Sample with Asymmetry > 0:</u>					
a) full sample	165	.69	.72	.72	.58
• t-ratio[2]		5.1	6.1	6.3	2.1
b) input cost share > .4	80	.69	.76	.70	.60
• t-ratio[2]		3.6	5.5	3.9	1.8
c) input cost share ≤ .4	85	.68	.67	.74	.59
• t-ratio[2]		3.6	3.3	.51	1.7
III. Mean Asymmetries by Industry of Output:					
• Food	36	**.168**	.086	.087	.142
• Textile/Leather	24	.087	.042	.032	.010
• Wood[3]	12	**.222**	.185	.124	.176
• Paper	15	-.124	**.273**	**.413**	**.434**
• Chemical	14	.129	**.263**	.173	.236
• Petroleum/Rubber	10	.008	.078	.111	-.099
• Non-ferrous metal	26	.060	.106	.115	-.027
• Steel	28	**.196**	**.187**	**.297**	**.331**

(numbers in **bold** indicate $|t| > 2.0$)

Note: Data come from VAR model. Results for distributed lag model mimic those shown here.

1. t-ratios for all mean responses exceed 6.6.
2. t-ratio is for difference from .5.
3. Includes one stone, clay, glass item

Table 5. Asymmetries in Response of Consumer Prices to Changes in Producer Prices

A. Mean Response Changes in Producer Prices

	Sample Size	Cumulative Response after Month:			
		0	1	3	5
1. Producer Price Change = +1	77	.194	.368	.482	.522
2. Producer Price Change = -1	77	.067	.159	.274	.336

B. Asymmetries in Response to Unit Changes in Producer Prices

	Sample Size	Cumulative Response after Month			
		0	1	3	5
I. Mean Asymmetry: (= panel A. line 1-line 2)	77	.127	.209	.209	.186
• t-ratio		5.4	5.3	4.4	4.0
II. Share of Sample with Asymmetry > 0	77	.766	.831	.740	.662
• t-ratio		5.5	7.7	4.8	3.0
III. Mean Asymmetries by type of consumer good:					
• Food – fresh	17	.016	.086	.097	.106
-processed	30	**.144**	**.289**	**.276**	**.251**
• Fuel	4	**.205**	.096	.069	-.036
• Furniture/Appliances	7	**.275**	**.355**	**.382**	**.446**
• Apparel/Jewelry	8	**.281**	**.285**	**.319**	**.339**
• Automotive	3	.066	.167	.141	.069
• Drug/Toiletry	4	-.036	-.013	.055	-.309
• Recreation	4	.031	.095	.000	.081

(Numbers in **BOLD** indicate |t| > 2.0)

Table 6. Asymmetries in Response of Prices at a Supermarket Chain to Changes in its Wholesale Prices

A. Mean Response to Wholesale Price Changes

	Sample Size	Cumulative Response after Month			
		0	1	2	3
I. UPC sample:					
1. Wholesale price change = +1	24	.593	.415	.565	.405
• t-ratio		3.9	4.7	4.8	6.1
2. Wholesale price change = 1	24	.585	.460	.394	.423
• t-ratio		6.0	3.8	5.1	4.9
II. Product average sample:					
1. Wholesale price change = +1	16	.445	.418	.473	.447
• t-ratio		4.2	6.7	6.8	6.7
2. Wholesale price change = -1	16	.447	.406	.461	.508
• t-ratio		7.6	5.0	6.1	7.1

B. Asymmetries in Response to Unit Cost Changes

	Sample Size	Cumulative Response after Month			
		0	1	2	3
I. Mean Asymmetry:					
a) UPC sample:					
(= panel A. line 1 - line 2)	24	.011	–.045	.170	–.017
• t-ratio		0.1	0.7	1.8	0.3
b) Product average sample	16	–.004	.016	.012	–.061
• t-ratio		0.0	0.2	0.1	0.7
II. Share of Sample with Asymmetry > 0:					
a) UPC sample	24	.42	.42	.58	.54
• t-ratio		0.8	0.8	0.8	0.4
b) Product average sample	16	.41	.53	.41	.65
• t-ratio		0.7	0.2	0.7	1.3

Table 7. Prices for Product Categories at a Supermarket Chain and Matched CPIs and PPIs

A. Annual Rates of Change over Sample Period

	Retail Prices: at supermarket	CPI	Wholesale prices at supermarket	PPI
Mean	2.0%	2.0%	1.5%	1.4%
S. Dev	4.1	1.6	4.1	1.9

B. Standard Deviation of Monthly Changes

	Retail Prices: at supermarket	CPI	Wholesale prices at supermarket	PPI
Mean	4.9%	1.0%	4.1%	1.2%
S. Dev	2.3	0.7	2.3	0.7

C. Regression coefficients: $y = a+bx$; y,x = mean annual rates of change

	b	$\lvert t\rvert$	s.e.e.
a) y = supermarket retail price x = matched CPI	1.18	2.3	3.8%
b) y = supermarket wholesale price x = matched PPI	.89	2.1	3.8
c) y = supermarket retail price x = supermarket wholesale price	.92	10.2	1.7

Note: Data are based on 23 supermarket product categories where it was possible to find a matching CPI or PPI. Missing values are replaced by column averages (for example, where the category has a matching CPI but not one or more of the other indexes). The supermarket prices are indexes of average product category retail or wholesale prices.

The sample period is September 1989 – September 1994.

Table 8. Independent Variables Used in Analysis of Asymmetries in Producer and Consumer Markets.

Variable and (Source)

A. **Input Price Behavior:**

Cost share: expenditures on the input per dollar sales of the output. For consumer goods expenditures and sales are those by retailers who specialize in the relevant merchandise line. Thus, fruit and vegetable store data are used for apples, though most apples are sold by supermarkets. (Producer goods: see appendix. Consumer goods: CR and unpublished data supplied by Census Bureau)

Standard Deviation: of the monthly change in the log of the input price index (PPI)

Drift: the mean monthly change in the log of the input price index over the sample period (PPI).

Persistence: estimate of the difference in the persistence of positive and negative cost shocks. For each input an autoregression is estimated with different terms for positive and negative cost shocks. Then responses to+1 and -1 initial shocks are dynamically simulated and cumulated over 8 months. This variable is the difference between the 8 month cumulative effects. Thus a positive number implies that positive cost shocks are 'more permanent' than negative costs shocks. (PPI)

B. **Input or Output Supply Industry (4 digit SIC which produces the input or output)**

Companies in this industry (CM)

Value of shipments by this industry (CM)

HHI: the Herfindahl Hirschman index of concentration for this industry (CM)

Finished goods/ship: the ratio of inventories of finished goods at manufacturing establishments in this industry to value of shipments (CM)

Raw materials/ship: ratio of raw material inventories to shipments (CM)

Assets/ship: ratio of gross book value of depreciable assets to shipments (CM)

Geographic concentration: sum over the nine census regions of | share of industry employment in region - share of population in region |. Minimum = 0 if employment is allocated exactly as population. Maximum = 1.9 if all production is concentrated in the least populous region (Mountain, with approximately 5 per cent of U.S. population). (CM)

Geog conc: out-in. sum of | share of output industry employment-share input industry employment | (CM)

C. Wholesale Industry (Consumer good sample only. 4 digit or higher SIC for kind-of-business which sells merchandise line including the good.)

Percent sales mfrs: percentage of all wholesale sales made by the manufacturers' sales offices or agents (CW)

Estab (non mfr): number of wholesale establishments which are not manufacturers' offices or agents (CW)

Sales (non mfr): wholesale sales by non-manufacturers (CW)

D. Retail market (Consumer good sample)

Consumer exp: weight of the good in the CPI-U index, December 1986 (BLS).

Stores: weighted number of stores handling the merchandise line including the good. Weights = (size of store type/size of type with modal sales). Example: apples are included in the 'fruit and vegetable' merchandise line which is sold by supermarkets, fruit and vegetable stores, etc. More fruits and vegetables are sold by supermarkets than other types of stores. Therefore, for apples, 'stores' = 1* supermarkets selling fruits and vegetables + (sales of fruits and vegetables per fruit and vegetable store/sales of same per supermarket)* number of fruit and vegetable stores + ...(CR)

Merch line sales: sales of the merchandise line.(CR)

Sales/inventories: sales of stores most heavily specialized to merchandise line divided by their inventories. For example, for apples fruit and vegetable stores rather than supermarkets would be used.(CR and unpublished data provided by Census Bureau).

Assets/sales: acquisition cost of depreciable assets/sales for stores most heavily specialized to merchandise line. (CR and unpublished data)

Sources:

All data are for 1987, the approximate mid-point of sample period, unless otherwise specified.

CM: Census of Manufactures
CW: Census of Wholesale Trade
CR: Census of Retail Trade. (Unpublished data are for 1992)
PPI: producer price index for the good (1978-96)
BLS: BLS Handbook of Methods, April, 1988

Some data for products of non-manufacturing industries were estimated or came from alternate sources as follows:

Agricultural products. U.S. Dept. of Agriculture, Agricultural Statistics, 1988 provides sales, output and some (farm) inventory data by commodity. Sales or output data are used for geographic concentration. Total farm sector asset/sales ratio is assumed applicable to each product, and total farm inventory/receipts ratio is used where commodity specific data are unavailable. Number of firms and HHI are set at the sample maximum and minimum respectively.

Crude oil. All data from Statistical Abstract of the U. S., except HHI which is assumed to be the same as for petroleum refining.

Scrap metal. All data from Census of Wholesale Trade, except HHI and assets/sales which are assumed equal to the sample average.

Table 9. Exploratory Regressions of Price Asymmetry Measures on Input Price and Market Characteristics Producer Goods

Asymmetry Estimate:												
Months	0	0	0	0	2	2	2	2	8	8	8	8
Type	DL	VAR	DL	VAR	DL	VAR	DL	VAR	DL	VAR	DL	VAR
Regression method	OLS	OLS	WLS	WLS	OLS	OLS	WLS	WLS	OLS	OLS	WLS	WLS
Independent variables:												
A. input price behavior												
cost share					**N**	N	n	n		N	n	**N**
ln standard deviation	**N**	**N**	**N**	**N**	n	n	**N**	**N**		**N**	**N**	**N**
drift					P	p			p			
persistence	**N**	**N**				p					p	P
B. input supply industry (SIC)												
ln companies	**P**	**P**	P	p							P	P
ln shipments	N	N	p	P					p	p	n	
ln HHI	**P**	**P**	**P**	P								
finished goods/ship							n				n	
geog concentration					**P**	P	p	p				
C. Output industry (SIC)												
ln companies	**N**	**N**	**N**	N	N		**N**	**N**	n		**N**	**N**
ln shipments	P	P	p	p	**P**	P	P	**P**	P	p	**P**	**P**
raw materials/ship					**P**	**P**		p	P	P		p
finished goods/ship			P	**P**			p	p				p
assets/ship			N	n	N	N	**N**	N			n	n
ln HHI	N	N	**N**	N			N	n	n		**N**	**N**
geog concentration	n		**N**	**N**	n	n						n
geog conc : out-in	n	N			**N**	N					n	n

Table 9 (Con't)

Note:

N (P) = coefficient is negative (positive) with |t|>2
N (P) = coefficient is negative (positive) with 1.5<|t|<2
n (p) = coefficient is negative (positive) with 1<|t|<1.5
a blank means |t|<1

Dependent variable in each regression is the estimated degree of asymmetry in the response of output to input prices. Sample = 165 producer goods. See Table 4 for summaries of this measure.

See Table 8 for description of independent variables.

DL (VAR) means that the asymmetry was estimated from a distributed lag (vector auto-regression) model.

Months denotes number of months' response of output to input prices in the asymmetry estimate. For example '8' means that the dependent variable is the estimated cumulative response from t=0 through t=8 to a unit input cost increase minus the estimated cumulative response over the same period to a unit cost decrease.

OLS (WLS) means that the regression here is estimated by ordinary least squares (weighted least squares). When WLS is used the weight is the inverse of the standard error of the coefficient of the first asymmetry term in the regression which produced the asymmetry estimate.

Each regression contains four dummy variables = +1 for non manufacturing industry groups (agricultural input, agricultural output, scrap metal input, crude oil input) where it was necessary to estimate some independent variables.

Table 10. Regressions of Price Asymmetries on Input Price and Selected Market Characteristics. Producer Prices

Independent Variables	Sample	All	All	All	cost >.4	cost >.4	cost >.4	cost <.4	cost <.4	cost <.4
	Lag	0	2	8	0	2	8	0	2	8
A. Input price behavior										
cost share		*	*	-0.27	-0.415	-0.323	0.619	*	*	-0.846
In standard dev		**-0.084**	**-0.096**	**-0.148**	**-0.2**	**-0.285**	**-0.359**	-0.036	-0.059	**-0.133**
B.Input supply industry (SIC)										
Ln companies		*	*	0.061	*	-0.058	0.067	0.061	0.07	0.13
Ln HHI		*	*	*	*	*	0.136	0.076	*	*
C.Output industry (SIC)										
Ln companies		-0.035	**-0.091**	**-0.173**	*	-0.106	**-0.227**	*	*	-0.165
Ln shipments		*	0.054	**0.113**	*	*	*	*	**0.063**	**0.168**
Raw materials/ship		-0.685	*	*	-2.62	*	*	-1.5	*	2.12
Assets/ship		*	-0.192	-0.189	0.266	*	*	*	*	*
Ln HHI		-0.03	-0.051	**-0.125**	0.076	**-0.188**	**-0.366**	*	*	-0.085
Geog concentration		**-0.097**	*	*	**-0.148**	-0.172	*	-0.06	*	*

Note: Coefficients shown in **BOLD** have |t|>2
Coefficients shown in LARGE have 1.5<|t|<2.0
Coefficients shown in SMALL have 1<|t|<1.5
* = Coefficient has |t|<1

See Table 8 for description of variables. Regressions are shown for the full sample of 165 producer goods ('All') and for subsamples of 80 (85) goods where the input's cost is greater (less) than .4 of the value of output. Each regression is weighted by reciprocal of the standard error of the first interaction term in equation (2). Equation (2) - the VAR model - is used to estimate dependent variables in this table.

Table 11. Exploratory Regressions of Price Asymmetry Measures on Input Price and Market Characteristics Consumer Goods

Asymmetry Estimate:						
Months	0	2	5	0	2	5
Regression method	OLS	OLS	OLS	WLS	WLS	WLS
Independent Variables:						
A. Input price behavior						
Cost share		n	n		p	p
Ln Standard Deviation	n	n	**N**	N	N	**N**
Drift					n	N
Persistence				**N**	N	p
B. Input producing industry						
Ln companies			p	**N**	N	
Ln shipments	n	n	**N**		p	
Ln HHI			**P**	n		**P**
Finished goods/ship			N		**N**	**N**
Geog concentration			n			
C. Wholesale industry						
% sales by mfrs					**N**	**N**
Ln estab (non-mfr)				p	**P**	**P**
Ln sales (non-mfr)			p		**N**	**N**
D. Retail market						
Ln consumer exp	p	p		p		
Ln stores			N			
Ln merch line sales			p			
Sales/inventories			**P**		n	
Assets/sales			N	p	p	p

Note: **N (P)** = coefficient is negative (positive) with |t|>2
N (P) = coefficient is negative (positive) with 1.5<|t|<2
n (p) = coefficient is negative (positive) with 1<|t|<1.5
a blank means |t|<1

Dependent variable in each regression is the estimated degree of asymmetry in the response of retail prices (as measured by a consumer price index) to producer prices for the same product. Sample = 77 consumer goods. See Table 5 for summaries of this measure.

See Table 8 for description of independent variables.

All asymmetries are estimated from a vector auto-regression model. See Note to Table 9 for definition of Months, WLS, OLS.

Each regression contains a dummy variable = +1 for unprocessed agricultural products for which it was necessary to estimate some independent variables.

Table 12. Regressions of Price Asymmetries on Producer Price and Selected Market Characteristics. Consumer Goods

Independent variables	Months' Lag 0	2	5
A. Producer Price Behavior			
Cost share	*	*	*
ln std deviation	**-0.067**	**-0.137**	**-0.134**
persistence	**-0.066**	**-0.064**	*
B. Producer Good Industry			
ln companies	**-0.061**	**-0.051**	-0.043
ln HHI	-0.031	*	0.063
finished goods/ship	-0.285	**-0.948**	**-1.328**
C. Wholesale Industry			
% sales by mfrs	*	**-0.644**	**-0.815**
ln estab (non-mfr)	0.063	**0.206**	**0.355**
ln sales (non-mfr)	*	**-0.141**	**-0.280**

Note: Coefficients in **BOLD** have |t|>2
Coefficients shown in LARGE have 1.5<|t|<2
Coefficients shown in SMALL have 1<|t|<1.5
* = Coefficient has |t|<1

Regressions are weighted by reciprocal of standard error of first interaction term in equation (2)
VAR model is used to estimate dependent variables

See note to Table 8 and Table 11 for description of independent variables and sample.

Appendix: The Three Price Samples

I. Producer Price Sample

My goal here was to find producer goods for which one other good is an important input. Importance is measured by the input's share in the value of output. For example, cattle are an important input in the production of beef. For this sample, both the input and output are producer goods whose prices are measured by a BLS producer price index (PPI).

I tried to match inputs and outputs at the least aggregated level permitted by the data. The PPI is gradually moving toward industry price indexes based on the standard industrial classification (SIC), but the bulk of historical PPI data is commodity price indexes. I used these commodity price indexes exclusively. They are classified by commodity codes unique to the PPI. As with the SIC, PPI commodity codes add digits to reflect more disaggregation. The highest level of aggregation is the 2-digit code (e.g. 01 = farm products). The finest level is the 8-digit code (e.g., 01310111 = choice steers).

Whenever possible I matched an 8-digit input to an 8-digit output. (For example, I could match the input; choice steers, to the output index 02210102 - USDA choice beef carcasses.) However the available data frequently dictated the use of 6-digit PPIs or, less frequently, 4-digit PPIs (in the preceding example, these would be 022101 - beef and veal and 0221 - meat). The only use made of 3-digit PPIs was to fill gaps in the more disaggregated indexes as described later. Occasionally I combined PPIs to fit the facts. (For example, urea-formaldehyde plastic resins are made of urea and formaldehyde. So I combined PPIs for the latter two using 1987 cost weights to provide the input index for the resin).

I began the search for input-output matches with the "use" table of the 1987 Input-Output Accounts of the U.S. Economy. This is a matrix based on the SIC. The 1987 version provides data for the approximate mid-point of my sample period. Each column of the matrix gives the share of one industry's shipments accounted for by purchases from each of the other (row) industries. These industries are at roughly the 3 to 4 digit SIC level, and on average each input-output industry produces around 10 of the 8-digit PPI commodities. From this Input-Output (IO) table, I selected all the entries where purchases from the input industry accounted for a least 20 percent of the value of the output industry's shipments (and both were commodities producing industries). Thus, I eventually matched choice steers to choice beef because the IO table first told me that purchases of "meat animals" account for .763 of the value of the shipments of "meat packing plants." The road from the crude matches provided by the IO table to the matches eventually used was provided primarily by the Census of Manufactures. This is also based on the SIC, and it provides the source material for the IO table. In addition, I used a mapping of PPI commodity codes into SIC industries provided to me by the BLS.

The Census' Industry Statistics gives disaggregated data (Table 6A) on the value of the products shipped (usually at the 7-digit SIC level) for each 4-digit SIC. It also gives expenditures by the industry on materials (Table 7) similarly disaggregated. The PPI - SIC mapping lists the PPI codes for all commodities produced by each 4-digit SIC industry. This enabled me to match the Table 6A output information and the Table 7 input data to specific PPIs. To illustrate with the running example: the Census Table 6A for SIC 2011 - meat packing plants gives the value of "whole carcass beef" (as well as "pork, primal cuts," etc.) shipped by this industry. Table 7A yields the industry's spending on SIC 013913, "cattle" (as well as 013933, "hogs", etc.). I then used the SIC-PPI mapping to translate the preceding into the specific PPI output-input match: 02210102 USDA choice beef carcasses / 01310111 choice slaughter steers and heifers.

Handling these data requires some irreducible use of judgment, common sense and general knowledge. For example, the researcher who does not know that beef is produced from cattle rather than hogs could go astray. For two groups of products, the matches came from information provided by industry experts. Roger Fisher, formerly of Amoco Chemicals provided information on the technology of producing plastic resins from basic organic chemicals. Donald Barnett, a steel industry consultant, F.M. Scherer, a renowned industry scholar, and J. Upton Hudson of U.S. Steel provided similar information on steel fabrication. The full sample undoubtedly contains some poorly matched inputs and outputs. However, the matching process preceded any data analysis, and I did not discard matches ex post because of apparently diverse price movements. A detailed listing of the input-output matches used in the study is available on request.

For each match I sought monthly data from January 1978 through June 1996. The start of the sample was dictated by revision of the BLS' methodology to emphasize transaction prices.[22] Some series contain one or more gaps. I usually filled these from changes in the series at the next level of aggregation (adjusted for differences in drift).[23] Thus, for example, I would try to fill a gap in 02210102 - choice beef with data from 022101 – beef. If that failed, I would use data from 0221 - meat. When a 4-digit series was unavailable and the gap was under 6 months, I filled the gap with log linear interpolation. I treated longer gaps as missing values. I dropped pairs if either series had less than 5 years of usable data.

I also dropped pairs if there were fewer than 20 input price changes. But this occurred very rarely. (These cases are in the detailed sample listing available on request.)

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[22] See BLS, Handbook of Methods, BLS Bulletin 1285, 1988, p. 126. Until 1978, PPI data were often unrealistically rigid because they reflected "list" prices rather than prices of actual transactions. A few of the series in my sample still look like list prices - a few changes punctuating long flat periods - but the vast majority do not.

[23] Specially, let

$\hat{m}_t$ = estimated change in the log of a series with missing values in month t, t = 1, ..., T

α_t = actual change in the log of a related series without missing values,

M, A= levels of the logs of the two series.

My estimate was:

$$\hat{m}_t = \alpha_t + \frac{1}{T+1}\left[\ (M_{T+1} - M_0) - (A_{T+1} - A_0)\ \right].$$

The last term on the right hand side is a constant equal to the average monthly difference in the change of the series I am estimating and the series providing the estimate.

For each input-output pair I estimated the fraction of 1987 output value accounted for by the input's cost. The 'default' estimate was the one provided by the IO table. Where possible, I used data in by Tables 6A and 7A of the Census of Manufacturers to refine this estimate. Thus, instead of IO data on meat and meat animals, I used spending on cattle per dollar of beef shipments for any beef output, spending on hogs per dollar of pork shipments was used for any pork output; etc. For plastic resins, I estimated the cost shares directly from 1987 prices and the underlying chemistry provided to me by Roger Fisher. In industries with substantial inter-plant transfers (e.g. paper, steel, non-ferrous metals) the cost share includes these transfers if the Census reports their dollar value.

II. Consumer Price Index Sample

I sought to match a consumer price index (CPI) for a specific product with the PPI for the same product. The main problem here is that the CPI and PPI do not share a common classification scheme, and there is no off-the-shelf translation from one classification system to the other. Accordingly, it was necessary to proceed product-by-product with heavy reliance on product descriptions.

While detailed exegesis of the difference between CPI and PPI classifications is unnecessary, a relevant "bottom-line" difference is that the CPI product definition is usually broader than the PPI's 8-digit commodity class. Specifically, there are around 450 six digit PPIs (and more than this at the 8-digit level) for finished consumer goods. By contrast, the finest disaggregation of the CPI yields only about 100 consumer goods indexes. So, it is often necessary to use the more aggregated (e.g. 4-digit) PPIs or to combine PPIs to obtain a match to a CPI index.

Another relevant difference is that the CPI classification system is not conceptually based on specific commodities or items. Instead it grows out of "expenditure classes" (EC) which are used to classify data from the consumer expenditure survey. The result is a 5-digit system with expenditures aggregated into 69 2-digit ECs. Each EC is disaggregated into 4-digit "item strata" each of which contains 5-digit "entry level items.[25]" (ELI). Thus EC 20 - Alcoholic Beverages includes 2005 - Alcoholic Beverages away from home, which includes 20051 - beer ale and other alcoholic malt beverages away from home. Often the item strata and ELIs coincide. So 2001 = 20011 – beer, ale and other alcoholic malt beverages at home. But, with some exceptions (called "special series"), the least aggregated indexes are at the 4-digit item strata level.

As the beer example suggests, even the 5-digit ELIs are rather broad categories. So what happens in effect is that the BLS field force ends up pricing draft beer in a Philadelphia bar, a bottle of beer in a Chicago restaurant, etc. to obtain the 20051 component of the 2005 index. Moreover, the identity of the specific products priced at a field office can change over

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[25] See US Bureau of Labor Statistics, BLS Handbook of Methods, Bulletin 2285, 1988 for further details.

time. Thus, the least aggregated CPI indexes typically include a changing variety of goods within an EC.

These conceptual differences between the CPIs and PPIs mean that only approximate matches between them are possible. Moreover, even if we can match the goods within a CPI/EC index with a PPI, the weights are not likely to match. In the preceding example, we can match EC 2005 - alcoholic beverages away from home to the PPI 0261 - alcoholic beverages. But this 4-digit PPI is an aggregate of 10 8-digit PPIs (bottled beer, ..., sparkling wines) and 3 6-digit PPIs (malt beverages, distilled spirit, wines). The weights used to aggregate these detailed PPIs come from the value of factory shipments, not from consumer expenditures in bars and restaurants.

Finally, there is a potential "slippage" in the match due to transactions with wholesalers. The PPI measures changes in ex-factory prices, which are not necessarily the same changes faced by a retailer who buys from a wholesaler. The same disjunction potentially arises in the producer price sample too. However, producer-to-producer transactions predominate in that sample.

These caveats understood, I matched CPIs and PPIs as follows: I began with least aggregated CPI index available; usually this was a 4-digit index or one of the special series. Then I sought the closest corresponding PPI or group of PPIs. This usually meant using some aggregate of 8-digit PPIs. Where feasible, I aggregated 8 digit PPIs (using PPI weights) instead of using the corresponding 6 or 4 digit PPI. For example, for the CPI for "living room chairs and tables" I aggregated the 8-digit "table" PPI and the 8-digit "chair" PPI. In this way extraneous items in the 6-digit "living room furniture" PPI (e.g. desks, cabinets) were excluded. Otherwise, 6 or 4-digit PPIs were used, or, sometimes, combined. I dropped items from the sample if they required adding PPIs from different 2-digit commodity codes to obtain a match. For example, I dropped the CPI for "sport vehicles and bicycles" which includes outboard motors, boats and bicycles[26]. Here, constructing a corresponding PPI is feasible, but this would entail too much aggregation for the present purpose. I also dropped CPIs where PPI data were too skimpy (due to the coverage of the available PPIs or gaps in the data).

As with the PPI sample, the construction of the CPI sample preceded analysis of the data, and a detailed list of the 77 CPI items included and the corresponding PPIs is available on request.

[26] The PPIs for these items can be found under the 2-digit codes for "machinery", "transportation equipment" and "miscellaneous" respectively.

III. Supermarket Prices

The second largest supermarket chain in the Chicago area, Dominick's, has been supplying weekly price and cost data to the University of Chicago's Graduate School of Business since September, 1989. The data are at the level of the Universal Product Code (UPC), i.e. a specific brand/package size like an 18 oz. box of Kellogg's Corn Flakes. They include all UPCs in 25 product categories comprising around 1/3 of storewide sales. Only packaged goods are included, so there are none of the more volatile meat, produce and dairy items.

There are nearly 100 stores in the chain, and every week each store supplies the retail price for each UPC in the sample. Each store is in one of four pricing zones. These zones are defined by expected long run pricing levels based on a combination of costs and competitive constraints. In three zones ("high", medium" and "low" price zones) the chief competitive constraint is provided by the largest chain in the Chicago area (Jewel). In the fourth zone, prices are constrained by a discount chain (Cub Foods). Prices for specific items can also vary among stores within a zone depending on local competitive circumstances.

In addition to the retail price of the UPC, the database includes the item's wholesale cost, which is a single, chain wide number. This feature makes the database useful for my purpose. However, the wholesale costs in the data do not correspond to replacement cost or to the last transaction price. Instead, we have the average acquisition cost (AAC) of the items in inventory.

This, of course, grates against what economists believe to be the relevant cost for rational decision making.

More precisely, the chain sets retail prices for the next week and also determines AAC at the end of each week, t, according to

$$\begin{aligned} AAC_t = {} & (\text{Inventory bought in t}) \cdot \text{Price paid}_t \\ & + (\text{Inventory, end of } t-1-\text{Sales}_t) \cdot AAC_{t-1} \end{aligned}$$

There are two main sources of discrepancy between replacement cost and AAC[27] The first is the familiar one of sluggish adjustment. A wholesale price cut today only gradually works itself into AAC as old, higher priced inventory is sold off. The second arises from the occasional practice of manufacturers to inform the buyer in advance of an impending temporary price reduction. This permits the buyer to completely deplete inventory and then "overstock" at the lower price. In this case AAC declines precipitously to the lower price and stays there until the large inventory acquired at that price runs off. Thus, the accounting cost shows the low price for some time after the replacement cost has gone back up.[28]

[27] The following is based on conversation with Mark Mrowiec of Dominick's.

[28] Though the path of economic cost here is not so obvious; selling off the large inventory frees up valuable storage space.

For my purpose, the salient problem with using AAC is that it is, in principle, affected by retail price changes. Moreover, the effect is asymmetric. The endogeneity arises because current retail prices affect sales and thereby movements in inventory. Thus, for example, a retail price reduction depletes inventory, and this raises the weight on newly acquired inventory in the calculation of next period's AAC. It can be shown that the combination of averaging and endogenous weights can induce spurious asymmetries in the estimated response of retail prices to measured wholesale price.

While caution is therefore warranted in interpreting the results, the measurement problem here needs to be put in perspective. Supermarket inventories turn over more than once per month, and I use data at monthly frequencies. So the typical weight on old prices in my cost estimates is likely to be small. Moreover there is evidence that the actual measurement problems are small. All of them imply an induced correlation between current retail price changes and future measured cost changes. (For example, sluggish adjustment of measured cost means that today's "true cost" will show up in future measured cost.) Accordingly, in preliminary work I added leads of wholesale cost changes to regressions including current and lagged cost changes. The frequency of significant coefficients on the leads was no more than would be expected by chance.

A change in manufacturer practice led me to terminate the sample period in 1994. Since then many manufacturers have adopted retrospective discounts: they announce a discount but deliver it via a rebate based on how many units of the item were actually sold to consumers in a specified period. This enables the vendor to limit arbitraging of geographic wholesale price differences. However, the chain's wholesale cost data fail to reflect these retroactive discounts.

The sample period is generally September, 1989 through September, 1994. I selected five UPC codes from each product category and collected their prices at four stores, one from each pricing zone. For each product category, the stores were selected randomly from within the group of stores ("control stores") not subject to a pricing experiment conducted by the chain over part of the period. The UPC codes were the five with the largest sales in the category.

The sample was modified to accommodate the following problems:

1. For some product categories, it was impossible to identify control stores for some zones. In these cases only 2 or 3 zones were sampled.

2. There are gaps in the prices. Their severity varies across categories and, sometimes, stores. If another store in the same zone sold a UPC at comparable prices, I used its price, if available, to fill a gap. Otherwise, if the gap was under two months, I assumed that the retail and wholesale prices remained unchanged. I treated longer gaps as missing values. Most of the longer gaps occur at the beginning of the sample period, because some product categories were added to the database after 1990.

3. Occasionally one of the five leading items in a category is either introduced or replaced well into the sample period. I replaced these with the next best-selling UPC that was sold continuously in the sample period.

The data are weekly, but I converted them into "monthly" (4 week) averages. I did this for comparability to the other samples in the study and to mitigate the aforementioned problems with use of AAC. More importantly, I used monthly data to reduce the impact of the temporary retail and/or wholesale price cuts ("deals") common to the supermarket industry. No simple time series model could capture adequately the mix of predictable, temporary price changes and the more durable less predictable changes in the weekly data. The latter are the more interesting for my purpose, and they predominate in monthly data.

I analyzed two kinds of price series:

1. UPC, store level data. Here I treat each UPC at each store as a separate sample. With 25 product categories and up to 4 stores and 5 UPCs per category, there are potentially up to 500 such "UPC, store" samples. I analyze 357 of these. As mentioned above, I was not always able to obtain 4 stores for every product category. In addition, because the goal of the inquiry is to measure response to price increases and decreases, I had to drop some UPCs because of an insufficient number of price changes. I dropped UPCs with fewer than 10 AAC changes in each direction. Because the data give AAC indirectly (we have retail price and "profit margin" = (Price – AAC) / Price), rounding error can induce spurious trivial price changes. So I adopted a de

minimus rule which treats AAC changes of less than 0.2 percent as no change. Since there are no more than 64 possible changes per series, my criterion for AAC changes is potentially stringent. Nevertheless, most UPCs met it. However, the criterion led to elimination of one entire category (cigarettes) and three (beer, frozen dinners and hot cereals) were each reduced to a single UPC by my criterion.

While I sample 4 stores per UPC, these are not 4 random draws. Each store faces the same wholesale price and their retail prices are set by Dominick's head office. This resuls in high correlation between price changes across pricing zones. Specifically, correlations of price changes for a UPC between stores in the high, medium and low zones are on the order of .8 or .9. This drops to around .6 for pairs including a 'Cubfighter' store. None of the analysis in the paper assumes that the 357 UPC, store samples are independent of each other.

2. Category average sample. For comparability with CPI and PPI data, I developed a sample in which the product category, rather than the store or UPC, is the unit of analysis. This was done by averaging across all the prices within a category as follows: first I converted each price series ($P_{i,j,t}$; i = UPC, j = store) into an index [$I_{i,j,t}$] with the mean $P_{i,j}$ = 100. Then I averaged the $I_{i,j,t}$ across the j stores for each i yielding a UPC index ($I_{i,t}$). The category index is then the simple average of the $I_{i,t}$ across the i UPCs in the category. This procedure gives each UPC the same weight in the index.

This sample contains 16 categories as compared to the 24 in the store, UPC sample. The 3 categories with a single UPC were dropped. Another 5 were dropped because the averaging left their AAC index with too many de minimus price changes.

The categories in the store, UPC sample were as follows:

Food Items

* ready to eat cereals *
* hot cereals *
* canned soup *
* tuna
* cheese
* cookies
* crackers
* snacks
* "front end" candy *
* frozen dinners *
* frozen entrees

Beverage Items

* beer *
* bottled juice
* frozen juice
* refrigerated juice