"Studying Price Markups from Stockout Behavior"

(Very Preliminary and Very Incomplete)

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Business cycle fluctuations exhibit important procyclical movements in hours and consumption. Market-clearing business-cycle models typically generate these opposite movements in leisure and consumption through very procyclical movements in the marginal product of labor. But empirically labor productivity is quite acyclical compared to movements in hours or consumption. This makes it difficult to rationalize hours fluctuations without market features that can drive a cyclical wedge between the marginal physical product of labor and marginal rates of substitution between leisure and consumption. (Hall, 1997, provides a thorough discussion of these issues.) This observation has helped renew interest in models with wage and/or price stickiness. Prices that are less procyclical than marginal cost can contribute to hours fluctuations by making labor's marginal revenue product more procyclical than its marginal physical product. Goodfriend and King (1997) show how sticky-price models contribute to hours fluctuations by creating countercyclical movements in price markups. Clearly purposeful movements in price markups can serve this role (e.g., Rotemberg and Woodford, 1999).

I exploit information on the frequency that products stockout, derived from the micro data underlying CPI measurement, to judge the cyclical behavior of price markups over marginal cost. Research in inventory behavior has been been motivated by related questions. For instance West (1990), Ramey (1991), Krane and Braun (1991), Kashyap and Wilcox (1993), Pindyck (1994), Bils and Kahn (2000), and Galeotti, et al. (2004) all use inventory movements to identify the structure of costs and nature of business cycle shocks. I argue that looking directly at stockout behavior has distinct advantages over studying inventories. One important advantage is that stockout information is potentially available for many goods for which data on finished inventories are not available.

In the next section I consider the production choice for a firm facing a constraint that sales cannot exceed the stock available (as in Kahn, 1987, 1992). By making one more unit available for sale, the seller increases sales in the event that a stockout occurs. To generate a predictable increase in the probability of stocking out requires: (1) a temporary increase in marginal cost (that is, an increase relative to discounted future marginal cost), or a decrease in the markup of price over marginal cost. Thus, given data on prices and interest rates, the expected likelihood of a stockout is directly informative on the behavior of marginal cost and price markups.

I present data on temporary stockouts for 63 distinct consumer durables in Section 3. The estimates are derived from information in the *CPI Commodities and Services Survey* (*CPI C&S Survey*), the monthly micro data underlying the Consumer Price Index. To calculate the CPI the BLS tracks a large set of prices, with each price specific to a particular product at a particular outlet. Only prices for products available for purchase are eligible for use in the CPI. For this reason, the *CPI C&S Survey* provides information for constructing occurrences of stockouts. Stockouts are quite common, occurring about 8% of the time for consumer durables. I depict how stockout frequencies differ across goods. I also examine to what extent stockouts increase, together with declines in price, over the shelf life of a product. I can use this information to judge the size of price markups over marginal cost across the consumer durables.

I examine the cyclical behavior of stockouts in Section 4. I find very little persistent or predictable movements in stockouts. Surprisingly, stockout rates appear to be very *acyclical*. This evidence runs counter past findings that suggest important cyclical movements in price markups over marginal cost as suggested, for instance, by models of price stickiness. Allowing for the impact of changes in real interest rates reinforces the picture of markups as not countercyclical.

Section 5 begins an analysis of how prices respond to stockouts. Conclusions do not yet follow.

2. Predicting Stockout Rates

Consider the production decision for a firm that produces to stock. In a pure production-smoothing model of inventories this decision is a pure cost minimization problem--firm's produce more today only if marginal cost is below expected discounted future marginal costs. Here I follow Kahn (1986, 1992), Thurlow (1993), and others by allowing a larger stock for sale to be potentially valuable by reducing the probability of losing a sale because of a stockout. The firm chooses output to maximize expected discounted profits subject to a constraint that sales cannot exceed the stock available.

$$(1)\qquad \underset{y_t}{max}\;\; E\Big(\sum_{i=0}^{\infty} \beta_{t,t+i}\big[p_{t+i}s_{t+i} - C(y_{t+i};\, \theta_t, \boldsymbol{w}_t)\big] \;\big|\; I_t\Big)$$

subject to:

$$(i)\qquad a_t = i_t + y_t = a_{t-1} - s_{t-1} + y_t$$

$$(ii)\qquad s_t = min\big[\, d(p_t, \boldsymbol{z}_t),\; a_t\big]\;.$$

An index for the particular firm's product is implicit. The expectation is conditioned on a set of variables I_t known when production is chosen for time t. s_t and p_t are respectively sales and price for t. All prices are relative to a numeraire good. p_t is an additional choice variable for the seller. But, I focus on the optimizing choice for output, given the observed price.[1] $C(y_t;\, \theta_t, \boldsymbol{w}_t)$ is the cost, in terms of numeraire good, of producing output y_t. It depends on a productivity factor, θ_t, as well as a vector of input prices, $\boldsymbol{w}_t$. Here forward, I write this as $C_t(y_t)$. $\beta_{t,t+i}$ denotes the real rate of discount for i periods ahead. For instance, $\beta_{t,t+1}$, which I denote β_t for convenience, equals $1/(1+r_t)$, where r_t is the real rate of interest (netting inflation in the numeraire's price) from t to $t+1$. For convenience, (1) assumes an infinite horizon. But in the empirical work I allow for the possibility that a good has a distinct product life.

Constraint (*i*) equates the stock available for sale to the beginning of period inventory plus the period's production. In turn, the beginning inventory reflects the unsold stock from the previous period.

Constraint (*ii*) states that sales are equal to the quantity demanded for the product $d(p_t, \boldsymbol{z}_t)$, if this demand is less than the stock available, a_t; but otherwise equals a_t. In addition to price, the quantity demanded depends on a vector of random variables $\boldsymbol{z}_t$, with at least one of these variables not contained in the information set $\boldsymbol{I}_t$.

I focus on the dynamic first-order condition to the problem in (1). Consider marginally increasing output for the firm in t, together with decreasing it in $t+1$, such as to keep the stock available in $t+1$ unaffected. Requiring this perturbation have no effect on expected profits yields

$$E\Big(-c_t + \mathit{\Gamma}_t p_t + (1-\mathit{\Gamma}_t)\beta_t c_{t+1} \mid I_t\Big) = 0$$

$$\text{where } \mathit{\Gamma}_t(a_t, p_t, \boldsymbol{z}_t) = I[d(p_t, \boldsymbol{z}_t) > a_t]$$

$\mathit{\Gamma}_t$ is given by an indicator function, equaling one in the event the product stocks out, and zero otherwise. The expectation of $\mathit{\Gamma}_t$ is the probability of a stockout. This first-order condition has the following interpretation. By increasing the available stock for sale by one unit, at a marginal cost this period of c_t, a firm increases sales by $\mathit{\Gamma}_t$. These sales are at price p_t. To the extent the increase in stock available does not increase sales, it does increase the inventory carried forward to $t+1$. This extra inventory can displace a unit

[1] p_t may or may not be contained in the information set I_t.

of production in $t+1$, saving its marginal cost c_{t+1}. This subsequent savings is discounted by β_t.

Rearranging gives

$$E\Big([\mathit{\Gamma}_t m_t + 1]\frac{\beta_t c_{t+1}}{c_t} \mid I_t\Big) = 1 \qquad (2)$$

where $m_t = (p_t - \beta_t c_{t+1})/(\beta_t c_{t+1})$. m_t is the percent markup of price in t over discounted marginal cost in $t+1$. I refer to this as the markup because $\beta_t c_{t+1}$ is the opportunity cost of selling a unit at date t. The term $\beta_t c_{t+1}/c_t$ reflects the growth rate of *real* marginal cost relative to a real interest rate.[2]

To predict an increase in stockouts requires either a predictable transient increase in marginal cost or predictable drop in the markup. A transitory increase in marginal cost, by raising the costs of accumulating inventory, makes it more costly to avoid stockouts. A lower markup reduces the benefit from selling the good, reducing firms' incentive to hold inventories to avoid stockouts. Thus predictable movements in stockouts provide information on the behavior of marginal cost and price markups.

In Bils and Kahn (2000) we relate the behavior of marginal cost and markups to predictable movements in inventory to sales ratios. We show that finished-goods inventories fail to move cyclically with expected sales, even though cross-sectional and low-frequency time-series data indicate that firms choose inventories to be proportional to sales. We find that important countercyclical movements in price markups over marginal cost are needed to explain this pattern. The information on stockouts from the *CPI C&S Survey* allows me to avoid assuming a specific functional form for how inventories affect sales, as was necessary in that work, or for how demand shocks affect sales, as required in Kahn (1987, 1992). Implications drawn from stockout behavior, as opposed to those based on inventory-sales ratios, are also more robust to assumptions on the technology for inventory holding, such as the importance of overhead inventories.

There are several assumptions implicit in (2) that should be highlighted. The first-order condition assumes strictly positive production of the good at time $t+1$. In the CPI data a number of goods become permanently unavailable at a retailer, typically replaced by newer product models. For this reason, in the empirical work I focus largely on stockout rates based only on observations that predate by several months prior the good becoming permanently (or seasonally) unavailable.

[2] $\beta_t c_{t+1}/c_t$ can be viewed equivalently as $1/(1+r_t^{mc})$, where r_t^{mc} is a real interest rate based on comparing a nominal interest rate to the rate of inflation in nominal marginal cost.

The analysis assumes that any demand not satisfied during t is lost to the firm. This is a natural assumption for non durable goods. For durable goods, the focus of the empirical work, this is less clear. For durables it is assumed that, in the event of a particular product stocking out, the consumer substitutes a competing brand or product.[3] (Studies by Emmelhainz et al., 1991, Fitzisimons, 2000, and Campo et al, 2003, report that the most common behavior of consumers faced with a stockout is to substitute a competing brand.) To the extent firms can recoup lost sales at a future date, the treatment in (2) overstates the cost of a stockout. Related, the data on stockouts I employ relate to a good being unavailable at a particular retail outlet. It is possible that, facing a stockout at one outlet, a consumer could purchase at another outlet. In this instance the data observation of a temporary stockout at an outlet does not correspond directly to the realization of $\mathit{\Gamma}_t = 1$ (a stockout) in equation (2). Or, also related, it is possible that a consumer could respond to a stockout by substituting another product from the same producer, but with possibly a different price markup. I return to these issues in the empirical work. Much of the empirical work can be generalized to allow for a fraction of stockouts to be recouped by the firm.

In going from the first-order condition in (2) to evidence of stockouts I am implicitly aggregating the producer and retailer's decision. That is, I am assuming the production decision is joint wealth maximizing for the producer and retailer. In the concluding section I discuss possible implications of deviating from this assumption.

Finally, it is useful to add an assumption that the random variable $[d(p_t, \boldsymbol{z}_t) - a_t]$ has a distribution that is continuous at the value of zero. The *CPI C&S* provides information on whether a product has a positive inventory. Observing no inventory in stock ($i_{t+1} = 0$) corresponds to the incidence of a stockout ($\mathit{\Gamma}_t = 1$) if there is a negligible probability that demand *exactly* equals stock available.

If we assume the two variables $(\mathit{\Gamma}_t m_t + 1)$ and $\frac{\beta_t c_{t+1}}{c_t}$ in first-order condition (2) are conditionally distributed jointly lognormal, then (2) can be written as

$$E\left(\mathit{\Gamma}_t m_t + ln(\frac{\beta_t c_{t+1}}{c_t}) \mid I_t\right) + \kappa \approx 0 \ . \qquad (3)$$

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[3] This might include the possibility that the consumer places an order for the product for future delivery from this or a competing seller. To the extent these orders are placed with the stocked-out store, equation (2) requires the "production to order" market be competitive. For instance, I might be willing to pay a markup to gain immediate posession of a book or exercise bike from a store. But, if the good is not available, that store will have to compete against more perfect substitutes (for instance, purchases over the internet) in the market for future delivery. (Relatedly, Kahn, 1986, discusses the impact of allowing rainchecks.)

The constant term κ reflects covariance between the two random variables. The approximation reflects replacing $ln(\Gamma_t m_t + 1)$ with $\Gamma_t m_t$. In steady state the ratio Γm equals a short-term real interest rate (plus perhaps short-term storage costs), putting it on the order of 0.01. So the approximation error should be very small. Much of the empirical work employs this form for the first-order equation.

The first-order equation links predictable variations in stockouts to variations in price markups and to intertemporal movements in costs. I use this equation in Section 4 to test hypotheses about the cyclical behavior of markups. Sbordone (2001), Christiano, et al., (2003), and Gali, et al. (2002) attribute little importance to cyclical movement in markups. If one assumes a constant markup in pricing this not only eliminates variations in the markup as an explanation for changing stockout rates, but also implies that intertemporal variations in marginal cost can be measured by intertemporal price movements. Substituting in equation (2) for a constant markup of price over the expectation of $\beta_t c_{t+1}$ yields

$$E\left([\Gamma_t m + 1] \frac{\beta_{t-1} p_t}{p_{t-1}} \mid I_{t-1} \right) = 1 \ . \qquad (4)$$

Thus a predictable increase in stockouts requires an opposite decrease in the good's rate of price inflation relative to the rate of interest, or equivalently, an increase in the good's own real rate of interest. Note that equation (3) does not depend on any particular specification of production or cost functions.[4]

By contrast suppose there are no *predictable* intertemporal fluctuations in (discounted) marginal cost, beyond that of an upward or downward trend in costs. This implies a constant expectation for $\Gamma_t m_t$. I use this prediction in the next section in order to gauge the magnitude of markups. I observe that the price of a specific consumer durable in the market falls over its shelf life, even well in advance of being discontinued at an outlet. I also observe a very predictable rise in the probability of the good stocking out temporarily. The constant expectation for $\Gamma_t m_t$ provides an estimate for the magnitude of the markup based on the (absolute) rate of decline in price relative to the rate of increased probability of stocking out over the shelf life of the item.

[4] The relevant information set for conditioning in equation (3) is that available when p_{t-1} is determined. For convenience, (3) assumes that price for time $t-1$ is determined at the same time (or with same information) as output for $t-1$. But the empirical work can allow for price to be determined subsequent (or prior) to output by conditioning on a broader (or narrower) set of variables than in I_{t-1}.

3. Stockout Patterns

Stockout information from micro CPI data

To calculate the CPI the BLS collects prices on about 90,000 non-housing goods and services per month with each price specific to a particular product at a particular outlet. About half of goods are priced monthly, with the others priced bimonthly.[5] These prices, and other information related to constructing the non-housing components of the *CPI*, are contained in the BLS' *CPI Commodities and Services Survey* (*CPI C&S Survey*).

A product must be available for purchase at the outlet at the time of visit by the BLS agent in order to be included in the CPI. If the product is unavailable for sale, the BLS agent is instructed to establish if the outlet expects to carry the item in the future. This information on product availability is contained in the *CPI C&S Survey*. I classify a product at an outlet as stocked out if it is not available for sale, it is continuing to be carried by the outlet, and it is not seasonally unavailable.[6]

Using the CPI data, I examine stockout rates for January 1988 through June 2004. I examine stockout rates for 63 separate categories of consumer durables as defined by BLS Entry Level Items (ELIs). In presenting results I typically aggregate the 63 ELI categories into 28 broader groupings to match detailed NIPA categories for consumer spending. The appendix table shows the BLS ELI's contained in each NIPA category. Table 1 provides the number of observations and CPI expenditure shares (based on 1997) for the ELI's within each NIPA category. The total number of observations (before sample restrictions discussed below) equals 999,432. The combined expenditure share for 1997 is 6.6 percent. Although this share is not particularly large, it should be kept in mind that spending on consumer durables is very volatile. So these goods provide a disproportionate share of cyclical fluctuations in consumer spending. Note that vehicles are not included among the consumer durables. Price quotes for vehicles are collected in a somewhat different manner than for most other consumer goods which precludes observing stockout rates.[7]

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[5] Prices are collected from about 22,000 outlets across 45 geographic areas. The BLS chooses outlets probabilistically based on household point-of-purchase surveys, and choose items within outlets based on estimates of their relative sales. The BLS divides consumption into 388 categories called Entry Level Items (ELIs). The BLS sampling methods are described in detail in Armknecht, et al. (1997) and the BLS Handbook of Methods (1997). For durables, the focus of the work here, about one third of prices are collected monthly, with the remainder collected bimonthly.

[6] Some products are unavailable to be priced because the entire outlet is not open. I do not count these as stockouts.

Stockout rates

Temporary stockouts are quite frequent. For the 999,432 observations, from January 1988 to June 2004, the temporary stockout rate averaged 8.8%. This weights all price quotes equally. For the balance of the paper, I construct stockout rates separately for each of the 63 expenditure (ELI) categories. I then weight each ELI's rate by its expenditure share in 1997.[8] This results in a weighted aggregate stockout rates of 9.2%. Studies of stockout frequencies have been largely based on supermarket data. For instance, Aguirregabiria (2003) cites a study by Anderson Consulting in 1996 showing a stockout rate of 8.2% across a sample of U.S. supermarkets.

The first-order condition (2) is derived assuming strictly positive production at $t+1$. For products near the end of their product life, this may not apply. The value of a stockout is presumably lower if the firm has a better (relative to cost) substitute coming on line. For this reason, for the balance of the paper I focus on stockouts that do not closely precede a product being classified as more permanently discontinued at an outlet, restricting attention to the observations that are three months or more prior to a product being permanently or seasonally unavailable.[9] I further restrict the sample to

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[7] A vehicle quote begins with a purchase invoice for a particular model at a dealer. At subsequent visits, the BLS agent inquires as to how price (incorporating rebates and financing discounts) have changed for that particular model. But, if that particular model had no sales at that dealership that period, then it is coded temporarily unavailable. Thus it is not possible to distinguish stockouts from zero sales.

[8] I first construct monthly ELI means then time aggregate to obtain each ELI's mean. Otherwise recent years be weighted more heavily, as the number of quotes collected has risen. The BLS selects outlets proportionally to their importance in a somewhat wider product category than an ELI, for instance, based on men's clothing, not the specific ELI men's shirts. For this reason, in constructing monthly ELI-level statistics, I weight by the percentage of sales within the broader category at the outlet corresponding to that ELI. The BLS refers to this percentage as the percent of pops category.

[9] This restriction alone yields a weighted stockout rate of 5.4%. The stockout rate in the the two months prior to a product becoming permanently or seasonally unavailable at an outlet is 35.0%. The stockout rate at 3 months prior, by sharp contrast, is only 10.0%. This is only modestly higher than the average stockout rate of 9.2% for 4 to 6 months prior to a product disappearing more permanently. The very high rate of tempory stockouts within two months of the product being more permanently unavailable may be exaggerated if BLS pricing agents initially misinterpret some more permanent product stockouts as temporary stockouts. A concern in the opposite direction is that some products that are repeatedly unavailable due to temporary stockouts become classified as permanently unavailable. This is a potentially bigger concern because, if a product is repeatedly unavailable, it may trigger an instruction to the field agent to substitute a new product version for pricing at the next visit. In practice, however, it appears that the field agents often continued to price the old version, usually because the product again became available for sale. (This is based on analysis conducted by Teague Ruder.) One further piece of evidence that this measurement problem is not overwhelming is that the stockout rate I find of 9.2% is even higher than the rate of 8.2 reported by Anderson Consulting for supermarket products.

observations that are followed by further appearance of the product at an outlet. That is, to be a temporary stockout the product must come back. In calculating stockout rates I eliminate both the first and final observations for the product because, by construction, stockout rates are zero for those observations. This results in an overall (weighted) stockout rate of 5.2%.

Stockout rates vary noticeably across consumer durables. Table 1 gives stockout results separately for the 28 categories of goods. (For goods categories that combine more than one BLS ELI, the stockout rates for the individual ELI's are weighted by their relative expenditure shares for 1997. The lowest stockout rates (0.7% and 1.3% respectively) are for tires and vehicle parts & accessories. The highest stockout rates (10.7% and 10.2% respectively) are for jewelry & watches and luggage.

Shelf-life changes in price versus stockouts

Equation (2) relates predictable changes in stockout rates to predicted changes in the markup and intertemporal marginal cost. In the next section this relationship is used to infer the cyclical changes in price markups. Note, however, that (2) suggests that, everything else equal, a one-percent *log* change in the markup implies an opposite one-percent *log* change in the stockout rate. For instance, an increase in the stockout rate from 5% to 6% would be implied by a 20% percent drop in the markup. But this 20% drop in the markup could reflect a drop from 6% to 5%, or from 30% to 25%. For discussing the impact of cyclical variations in price markups, a drop in the markup from 30% to 25% is five times as important as a drop from 6% to 5%, as it reflects five times as large of a drop in the implicit tax of the price-markup on turning leisure into consumption.

One can potentially gauge the size of the markup from a reverse exercise: If we observe a particular-sized change in price relative to marginal cost, what percent impact does this have for the probability of stocking out? The answer reflects the size of the markup. Durable goods show predictably sharp declines in prices over the life of a product model (e.g., Bils, 2004, finds that durable prices for this time period declined about 3.3% annually between product substitutions.) I examine how stockout rates predictably change over time on a particular product at an outlet in conjunction with predictable declines in price.[10]

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[10] In principle it is possible to gauge the size of markups just from the uncondtional expectation in equation (2). This implies that the markup should be equal to the real interest rate for a good (defined by netting the average rate of growth in marginal cost for the good from a nominal interest rate) divided by the stockout rate. If the interest rate is measured by the one month commercial paper rate and one assumes that the rate

Taking *unconditional* expectations of the first-order condition in (3), then first differencing with respect to time yields

$$E\Big(\varDelta(\varGamma_t m_t) + \varDelta ln\big(\frac{\beta_t c_{t+1}}{c_t}\big)\Big) \approx 0 \ .$$

where $\varDelta x_t$ denotes the time difference in variable x_t. The second term is the rate of acceleration in (discounted) marginal cost. If we assume that the rate of growth (or decline) in marginal cost is constant over the product life, then the expectation of this second term is zero, implying that the multiple $\varGamma_t m_t$ is expected to remain constant over the life cycle of the product. Making this assumption and expressing $\varDelta(\varGamma_t m_t)$ in terms of changes in $\varGamma_t$, p_t, and marginal cost yields[11]

$$(5) \qquad E\Big(m_t \varDelta\varGamma_t + \varGamma_t(1+m_t)\big(\frac{\varDelta p_t}{p_t} - \frac{\varDelta(\beta_t c_{t+1})}{\beta_t c_{t+1}}\big)\Big) \approx 0 \ .$$

Based on (5), I proceed to calculate the average increase in stockout rate and the average rate of decrease in price relative to (a proxy for) marginal cost as a product remains for sale at a particular outlet. (5) implies the magnitude of the markup can be gauged by requiring that the rate of fall in price relative to marginal cost imply a rate of drop in the markup equal to the rate of increase in the stockout rate. For instance, if *changes* in markup rates are nearly orthogonal to *levels* of markups and stockout rates, then (5) implies

$$(6) \qquad \frac{\bar{\varDelta}\varGamma}{\bar{\varGamma}} \approx -\frac{1+\overline{m}}{\overline{m}}\big(\frac{\varDelta\overline{p}}{p} - \frac{\varDelta(\overline{\beta}c)}{\beta c}\big)\Big) \ .$$

where a bar above a variable implies its average over the product life.

Table 2, Column 1, reports the weighted average monthly change in stockout rates and price over the durable goods. The monthly change in stockout rates is an increase of 0.37 percentage points (with standard error of 0.02 points.) This monthly change is equal to 7.3% of the average rate of stockouts. The average price change is a decrease of 0.36 percent (with standard error of 0.008 percent). A selection problem exists in that prices are usually not observed if the product stocks out. Since stockout rates increase as the

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of growth in marginal cost equals, on average, the rate of price inflation, this implies a monthly real interest rate of .05%. Given a stockout rate of 5.2%, this is consistent with a markup of a little less than 10 percent. But there are several holes in this calculation. The rate of inflation is likely to be significantly lower than the rate of increase in marginal cost for a product, once it is on the market. This calculation also ignores storage costs, which are difficult to measure. Finally, this assumes any stockout is lost in terms of sales.

[11] This assumes small changes, so that second-order terms in the changes in rates of stocking out and changes in markups can be ignored. For the monthly-frequency data this should be appropriate.

product life ages, this selection problem grows. The results for price change are not very sensitive to this problem, as the increase in stockout rates (0.37 percentage points per month) is not large enough to exhibit much effect. Furthermore, in calculating average price changes I include the price observation when the product returns from stockout (even though stockout rates are not based on the last time the product is observed.) So even if a potential price cut is not captured coincidentally with a stockout, its impact on price trends is captured when the product returns.[12]

To employ equation (6) requires information on how the markup of price over marginal changes as shelf-life ages; so it is necessary to net the rate of growth in marginal cost from the rates of price change over the product life. A higher rate of growth in marginal cost implies a faster decline in the markup and, given the rate of increase in stockouts, a higher markup. It is difficult to measure the rate of growth in marginal cost for a static, unchanging product. I try two proxies. Fortunately most calculated markups are not overly sensitive to these choices.

I first assume that productivity is simply constant as the product ages. This is consistent with established products exhibiting no technological change together with constant returns. The growth rate in marginal cost can then be related to rates of growth in input prices. For now, I focus on the rate of growth in wage rates and materials deflators for durable manufacturing for 1988 to 2001. (The source is the BLS data from the program on *Major Sector Multi factor Productivity*.) The monthly growth rate in wage rates averaged 0.30 %, that for materials prices 0.07%. These imply a rate of growth in marginal cost of 0.22% monthly using 1997 cost shares of 63% and 37% respectively for labor and materials. I use this same rate of change in factor prices for each of the 28 goods' categories. (This can be relaxed in future drafts.)

This measure presumably overstates the rate of growth in marginal cost, as we would expect some productivity growth for products over their shelf lives. As a second measure, I assume that static (unchanging) products exhibit one-third the trend productivity growth in a sector. I set the level of trend productivity growth so that the average rate of growth in marginal cost in a good category (equal to the rise in input

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[12] Interpolating for the missing prices based on estimated projections on lagged and future prices has no impact on the estimates in Table 2. For about 10 percent of stockouts (3749 cases), the CPI C&S Survey report the collected price, even though it is not employed in the index. So it is possible to see how the prices at stockout dates systematically differ from prices without stockout dates. The prices at stockout dates are significantly lower than *average* prices for the good, but conditioning on the lagged observed price, I estimate the price is only one tenth of one percent lower than predicted based on periods without stockouts. (This effect is not statistically significant.) .

prices of 0.22% monthly minus the rate of productivity growth) is equal to the rate of price increase for that category. This assumes no important trend in the markup over the 15+ years from 1988 to June 2004. The average rate of price increase is measured by inflation in the NIPA deflator, reported by good in the third column of Table 3. Allowing for one-third of productivity growth to accrue to established products lowers the average monthly rate of growth in nominal marginal cost across the goods from 0.22% to 0.07%.

Taking the average monthly changes in stockout rate (0.37 percentage points, 7.3% of the average stockout rate) and in price markup ($-$ 0.58%) across the 28 goods and employing equation (6) implies a modest markup of 8.6%. The standard error on this calculated markup is approximately 0.5%. The second markup reported in Table 2, Column 1, assumes that static goods exhibit one third of the long-term productivity growth calculated for that category of good. This reduces in magnitude the average monthly change in the markup level from $-$ 0.58 to $-$ 0.43%. This reduces the calculated markup from 8.6% to 6.3%.

The sharp increase in stockout rates with product life, and the small markups implied, do not reflect extreme stockout rates at the end of products' lives. The estimates are based on observations at least 3 months prior to the model disappearing for more permanent reasons and requires the product model return from stockout. But for convenience this calculation assumed that changes in markup rates are orthogonal to levels of markups and stockout rates. In fact markups appear to fall more rapidly later in the product cycle, when markups are relatively low and stockout rates relatively high. This is illustrated in the second and third columns of Table 2. Here for each product model, I break its sample period into beginning and latter halves. The absolute increase in stockout rates is nearly three times larger in the later stage, and more than twice as large relative to the level of the stockout rate (increasing 4.5% monthly in the first half, but 9.4% in the latter half). Price also drops somewhat more sharply in the later stage, falling 0.42% per month, rather than 0.32%. The markup, calculated under no productivity growth, is 13.7% for the earlier product life, but only 7.2% in the latter. This suggests an average markup of about 10.5%, somewhat higher than the 8.6% in the first column. Allowing for productivity growth for existing products, equal to one-third of overall productivity growth, yields markups averaging 9.6% early for the product, and 5.4% nearer the end of the product's shelf life.

Notice that the drop in markup between the first and second halves of a product's observed sample period is entirely consistent with how the level of the markup is being calculated. For instance the fall in markup from 13.7% in the first half to 7.2% in the latter half would require a drop in price minus marginal cost of 5.3% between the first and second halves. The average aging between the two halves is 8.9 months. With price falling by 0.58% per month relative to marginal cost, this would generate a drop of 5.2% over the 8.9 months. This is almost precisely the drop implied (5.3%), independently, by calculating the markups separately for the earlier and later stages of the product lives.

A key simplifying assumption made here is that a stockout results in a lost sale. If we allow for a fraction of sales to be recouped at the posted price, the analysis carries through. Even though the stockout rate exaggerates the frequency of lost sales, the rate of change in the stockout rate captures the rate of change in lost sales.[13]

A bigger concern is if consumers substitute an alternative model by the producer with a different price, where the price departs from that for the stocked out product in a systematic fashion over the product cycle. Suppose that x percent of stockouts result in consumers substituting an alternative product from the same brand. And suppose, as an extreme case, that the price of the substituted same-brand product is independent of the product life (and fall in price over the product life) of the stocked out good. Then the calculations above will understate the markup by a factor of x. But is important to recognize that a significant fraction for x is not consistent with the *changes* in the markup calculated between the first and second halves of a product's sample period, reported in Columns 2 and 3 of Table 2. As an example, suppose x equals one half. Then the markups reported in Table 2 are biased down by half. But if we double the reported markups, this would imply a fall in the markup from 27.4% to 14.2% over the brief period, averaging 8.9 months, between a product's first and second halves of its sample period. Even allowing for no productivity growth, this would require that products fall in price by more than one percent per month, which is extremely counterfactual. More generally, requiring consistency of the *change* in the markup over the product life with the observed fall in product price makes it difficult to rationalize markups much greater on average than 10 percent.

The results in Table 2 use data aggregated across goods. Table 3 presents results separately across the 28 goods categories. The first column reports the average monthly change in stockout rate as product life ages. The average change is positive for 27 of the

[13] Alternatively, suppose that consumers make multiple searches. An effective stockout corresponds not to the event of a stockout at one retailer, but when a consumer stops searching for the product. Note, however, that this suggests that effective stockout rates are even more responsive to changes in markups. As an illustration, suppose that consumers are willing to search two time for the product and that stockout probabilities are independent across these searches. Then the probability of an effective stockout would be measured by the outlet-probability squared. This implies the percent change in effective stockout rates (the left side of equation (6)), would be double what I have reported. In terms of equation (6), this would cut the calculated markup by half.

28 categories. This change is statistically significant with a p-value below 0.05 for 15 of the categories. The next column reports the average monthly change in nominal price as shelf life ages. Price falls on average for 25 of the 28 categories, and for two of the remaining three categories the average increase is very close to zero. The declines in dollar price is statistically significant with a p-value below 0.05 for 21 of the categories.

Markups calculated separately by good appear in the final column of Table 3. For the most part the markups are reasonably low. Using a common rate of growth in marginal cost of 0.22% per month, based on no productivity growth, the median markup (unweighted) across the goods is 6.8%. An exception is the goods' category of audio disks and tapes, which shows a markup of infinity, and computer software and accessories, which shows a markup of 163%. (The median standard errror for the markups across the goods is about 2%, but the standard error for the markup for these goods is considerably larger.) These markups for software, video equipment, and computers are probably biased up, as the assumption of no productivity growth in these products, once it reaches the market, is probably unreasonable. The second markup reported in Table 3 assumes that static goods exhibit one third of the long-term productivity growth calculated for that category of good. The median calculated markup across the goods falls from 6.8% to 6.0%. The calculated markups are considerably smaller for computers, computer software and accessories, and video equipment.[14]

These calculations take the rapid rise in stockout rates over the product life as evidence against high markup rates. The related point I wish to stress is that, based on the product life, stockout rates are quite responsive to markup changes.

4. Cyclical Fluctuations in Stockouts

Figure 1 graphs monthly stockout rates, combining all the durables, for January 1988 to February 2004. (Individual stockout rates for the 63 ELI categories are aggregated monthly, weighting each ELI by its 1997 expenditure share.) As before, stockouts are based on observations at least three months prior to the product being permanently unavailable and must subsequently return. (Also the last four months of the

[14] It should be kept in mind that combining all calculating a single markup, as opposed to breaking it into early and late stages for the product, probably understates somewhat the average markup for most goods.

sample are cut off.) The stockout rate is seasonally adjusted.[15] The figure plots stockout rates both excluding and including computers and equipment. There are spikes in stockout rates for computers in a couple of months, particularly July 2001. For the remainder of this section, when aggregating I focus on the series excluding computer equipment. But all statements below about persistence and cyclicality of stockout rates go through quite closely if stockout rates for computers and equipment are included.

Stockout rates show very little persistence. Figure 1 shows a clear increase in stockout rates over the sample period. It equals 4.6% during the first half of the sample; 6.1% for the second half. This creates the semblance of persistence in the stockout series; it exhibits autocorrelations of 0.46 at one month and 0.42 at four months. If low frequency movements are removed, taking out a Hodrick-Prescott trend, this persistence is eliminated. The autocorrelation is 0.11 and 0.05 respectively at lags of one and four months. (By contrast, these autocorrelations in hours in durable goods manufacturing are still 0.84 and 0.5 after removing an HP trend.) When I disaggregate to the good category, stockout rates still show little persistence. By contrast, there is important persistence in stockouts for a product at the level of a retail outlet. Conditional on observing no stockout for a product at an outlet in the current month, the frequency of stockouts two months later is only 4.3 percent. But conditional on a stockout this month, the frequency of a stockout again for that product 2 months later is 25.0 percent.

Figure 2 plots the stockout rate (without computers) together with HP-filtered aggregate hours in durable-goods manufacturing. The index of hours is taken from series generated by the BLS from the Current Employment Survey. Note that durable-goods manufacturing is much broader than the consumer durables represented in the stockout rates. Below I also consider narrower measures based on real consumption of these durables.

The stockout rates are very acyclical. Table 4, Column 1, reports the results from regressing the stockout rate, HP filtered, on HP-filtered hours lagged one month. (This allows for the possibility that the information set when choosing stock available in month t does not include hours in t. But results are virtually the same if lagged hours are replaced with current.) The estimated relationship to stockouts is zero, and estimated

[15] The most striking seasonal is for January, when stockout rates are 30% above the average for the year (6.8% compared to 5.2%). Stockout rates are about 10% below normal in May and 15% below normal in November.

reasonably precisely. Stockouts are also acyclical if we judge the cycle by the rate of increase in hours, or workweeks.[16]

The relationship between stockout rates for the 27 goods, excluding computers, and real expenditure on these durable goods (HP filtered) are given in the second column of Table 3. Monthly real expenditures for these goods are taken from the NIPA accounts, personal consumption expenditures by detailed category. Given sales are not determined at the time of production, I project the stockout rates on real expenditures lagged by one month. The results show a negative relationship between last month's real expenditure and this month's stockout rate. The stockout rate and aggregated real expenditure on the 27 durables is plotted in Figure 3. There are persistent movements in real consumption spending, but not in the stockout rate. Finally Column (3) relates the stockout rate to growth rates in the aggregated real expenditure for each of the last two months as well as the level of (HP-filtered) real consumption 3 months prior. Stockouts do not increase even with recent high growth in expenditures.

These results do not exploit the different cyclical patterns in stockout rates or consumption expenditures across the goods categories. Table 5 presents results separately by goods category. The first column defines the cycle by aggregate movements in hours in durable goods manufacturing. No category shows procyclical stockouts with the cycle defined this way. The second column looks at HP-filtered real expenditure, lagged one month. For the most part, stockout rates appear to show little cyclical pattern.

The lack of persistence or clear cyclicality in stockout rates may suggest that markups exhibit little persistent or cyclical movements. But this is dependent on knowing the cyclical behavior of intertemporal movements in marginal cost. For instance, if marginal cost rises rapidly, relative to the real interest rate, in boom times, this could imply an acyclical stockout rate even if markups are countercyclical.

Under a constant markup, the combination $\Theta_t = \mathit{\Gamma}_t m + ln(\frac{\beta_{t-1} p_t}{p_{t-1}})$ should have a constant expectation (combining equations (3) and (4)). The latter term is just the negative of a good's own real interest rate. The weighted aggregate of this real interest rate across the 27 goods (excluding computers) is presented in Figure 4 together with the aggregated stockout rate. The real interest rate is based on the one-month commercial paper rate (source is Federal Reserve Board) and each good's NIPA rate of price inflation. The figure, more precisely, presents the expectation of the real interest rate based on six lagged values of the real rate, the current commercial paper rate, and six lags of inflation

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[16] The estimated coefficient for the rate of growth in hours it is $-.075$ (.057); and for the one-month lagged workweek it is $-.107$ (.068).

rates and is annualized for the figure. This measure of the real interest rate is actually procyclical. A one percent increase in aggregate hours in durable good manufacturing is associated with an increase in the real interest rate of .045% (with standard error .011%).

Figure 5 considers further the evidence for a constant expected markup. The combination Θ_t, which should be *i.i.d.* under the constant markup conjecture and rational expectations, is plotted for two values of the markup, 10 percent and 50 percent. The evidence from Section 2 is suggestive of a value of 10 percent, or perhaps even less. With a 50 percent markup, the combination Θ_t inherits much of the behavior of the stockout time-series. In particular, it trends up over time, with a mean value of 2.30% in the second half of the sample, compared to 1.82% in the first half. Without filtering, it displays one and four month autocorrelations of 0.39 and 0.34. With a markup of only 10 percent stockout probabilities play a smaller role, relative to real-interest rate considerations, in the inventory decision, and so have less impact on Θ_t. The series for Θ_t under the lower markup shows no trend over the sample, equaling -0.01% in the first half and 0.001% in the second. It shows little persistence, even without filtering, displaying one and four month autocorrelations of 0.12 and 0.18.

The cyclicality of the combination $\Theta_t = \mathit{\Gamma}_t m + ln(\frac{\beta_{t-1} p_t}{p_{t-1}})$, under a 10 percent markup, is presented in Table 6. Θ_t, largely inheriting the (opposite) behavior of the real interest rate, is counter cyclical. From Column 1, a one-percent increase in aggregate hours from two months prior is associated with a decrease of 0.050 percent in Θ_t (with standard error 0.012 percent).[17] Defining the cycle by real expenditure for the 27 durables, Column 2, provides a similar picture: A one-percent increase in real expenditure two months prior is associated with a decrease of 0.043 percent in Θ_t (with standard error 0.013 percent). The third column breaks real expenditure into its recent growth and value 4 months prior. Θ_t continues to appear counter cyclical.

The counter cyclical pattern in Θ_t shown in Table 6 constitutes a mild rejection of a constant markup. Notice that to create an error in the first-order condition (3) that is *i.i.d.* would require deviating in the direction of a pro cyclical markup. Thus this is further evidence against the presumption of a counter cyclical markup.

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[17] I lag hours and consumption one additional month, as it is not clear hours or consumption at $t-1$ are available at the time of determining period $(t-1)$'s stock available.

5. Price Responses to Stockouts

The data show a lack of cyclical movements or even important persistent movements in the stockouts. This holds at the good category as well as for all goods aggregated. This raises the question of how the market responds to a positive innovation in stockouts such as to eliminate a persistent increase. One possibility is that stockouts reflect very transitory surprises in sales. But the persistence in sales makes this unlikely. Other possibilities are some combination of increases in prices or production. In this, very preliminary, section I examine how prices respond to stockouts.

Table 7 reports how price paths surrounding stockouts systematically differ from observations without stockouts. The first row reports a regression of the rate of price change from four months prior on whether a stockout occurs at the observation two months before. Examining the change in price after a stockout is confounded by the fact that, conditional on a stockout, a price is typically not collected. So the label impact after a stockout is somewhat misleading. This would only be true if the price observed two months prior to the stockout is a good indicator of the price at stockout. I find that observing a stockout is associated with a slightly greater rate of price increase over the four month period. It is associated with both more frequent price increases (by 2.0%) and price cuts (by 1.0%). It is also associated with price changes of greater magnitude.

More clear cut is the behavior of prices over the period preceding a stockout. Price increases by 1.1% less prior to a stockout. Prices are nearly 3% more likely to have been cut and, conditional on a cut, are decreased by 4% more. Price increases are a little less likely prior to a stockout; but, conditional on occurring are larger than typical prior to no stockout.

Based on Table 7, the evidence is mixed on whether stockouts should be viewed as accompanying price increases or decreases. The rate of price increase from month $t-4$ to t is very slightly positively related to the event of a stockout at month $t-2$, with an impact of 0.19% (standard error of 0.10%). But if we take a slightly longer window, from $t-6$ to t, the impact of a stockout at $t-2$ is slightly negative, equaling -0.24% (with standard error of 0.12%).

There is little evidence that stockouts primarily reflect price stickiness. Among all products for which price data is available at months $t-4$ and $t-2$, the average (weighted) stockout rate is 4.3%. For those with no price changes between months $t-4$ to t, the rate is slightly lower, equaling 4.2%. It equals 3.7% for those exhibiting price increases from $t-4$ and $t-2$; it equals 5.3% for those exhibiting price decreases. If we take a longer view, from months $t - 6$ to t, the picture is similar. Products with no price change show a stockout rate of 4.1% compared to an overall rate of 4.2%.

6. Conclusions

Table 1: Stockout rates by Durable Good

NIPA Good	Obs	Expend Share	Stockout rate
Tires	64,158	.290	0.7
Vehicle accessories & parts	58,171	.260	1.3
Furniture, mattresses & springs	103,222	1.184	3.8
Major household appliances	35,885	.271	3.5
Small electric appliances	33,697	.241	6.7
China, glassware, tableware & utensils	44,478	.177	4.5
Televisions	28,300	.269	4.7
Video equipment and media	23,921	.230	6.4
Audio equipment	20,185	.162	4.8
Audio disks & tapes	18,636	.179	5.3
Musical instruments	17,387	.064	3.4
Computers & equipment	6034	.488	7.9
Software	10,075	.067	5.0
Floor coverings	17,373	.095	1.8
Clocks, lamps, & furnishings	35,406	.336	5.1
Window treatments	20,224	.095	3.2
Writing equipment	3479	.018	4.5
Tools, hardware & supplies	33,560	.200	3.3
Outdoor equipment & supplies	11,776	.145	5.2
Sporting equipment	50,582	.319	8.0
Photography equipment	10,579	.042	4.2
Bicycles	6010	.047	5.5
Pleasure boats	16,846	.227	7.1
Jewelry & Watches	93,512	.470	10.7
Luggage	8189	.034	10.2
Semidurable house furnishings	34,116	.259	6.0
Medical goods	7972	.021	4.2
Toys, dolls & games	33,130	.409	6.8
All	**847,493**	**6.602**	**5.2**

Data: *CPI Commodities and Services Survey*.

Stockout rate (and # observations) is for 3+ months prior to being permanently or seasonally unavailable.

Table 2: Shelf-life Changes in Stockout rates and Prices With Implied Markup

	Over Product's Whole Sample	Over 1st half of Product's Sample	Over 2nd half of Product's Sample
Average stockout rate	5.00 (.020)	4.26 (.026)	5.70 (.030)
Monthly change in stockout rate	0.37 (.020)	0.19 (.027)	0.54 (.030)
Rate of change in stockout rate	7.3% (0.39)	4.5% (0.64)	9.4% (0.50)
Monthly rate of change in price	− 0.36 (.008)	− 0.32 (.011)	− 0.42 (.012)
Markup with no productivity growth	8.6% (0.51)	13.7% (2.24)	7.2% (0.43)
Markup with productivity growth pass through of 1/3	6.3% (0.38)	9.6% (1.53)	5.4% (0.33)
Observations	732,047	358,862	373,185

Data: *CPI Commodities and Services Survey*.
Observations are for 3+ months prior to being more permanently unavailable.

*The first markup assumes no productivity growth--yields a monthly growth rate of marginal cost of .215% (from wage-growth .2974%, materials prices .0740%, with respective costs shares of .632 and .368). The second markup assumes a productivity pass through of 1/3; marginal cost grows at .07% per month.

Table 3: Product-life Changes in Stockout rates and Prices by Durable Good

NIPA Good	Δ Stockout With age	Δp/p With age	Good's average Δp/p	Implied markups
Tires	.02 (.05)	−.02 (.02)	.02	8.2 / 5.8%
Vehicle accessories & parts	.05 (.06)	−.03 (.02)	.04	6.8 / 5.1
Furniture, mattresses & springs	.23 (.05)	−.13 (.02)	.03	5.3 / 4.4
Major household appliances	.22 (.08)	−.19 (.02)	−.05	5.8 / 4.5
Small electric appliances	.16 (.11)	−.38 (.03)	−.22	29 / 20
China, glassware, tableware, utensils	.14 (.09)	−.09 (.04)	−.05	10 / 7
Televisions	.60 (.11)	−.67 (.03)	−.52	6.7 / 4.7
Video equipment and media	.52 (.15)	−1.00 (.04)	−.84	17.2 / 11.6
Audio equipment	.60 (.13)	−.67 (.04)	−.22	7.3 / 6.0
Audio disks & tapes	−.09(.15)	−.05 (.05)	.02	X
Musical instruments	.15 (.11)	.02 (.03)	.02	4.4 / 2.9
Computers & equipment	1.06 (.30)	−1.60 (.09)	−2.24	14.4 / 7.4
Software & accessories	.06 (.19)	−.60 (.08)	−1.35	163.2 / 28.4
Floor coverings	.13 (.08)	−.01 (.04)	.14	2.9 / 2.5
Clocks, lamps, & furnishings	.20 (.10)	−.42 (.04)	−.17	17.5 / 13.5
Window treatments	.31 (.09)	−.13 (.07)	−.09	3.2 / 2.2
Writing equipment	.36 (.31)	−.33 (.08)	.43	6.8 / 7.7
Tools, hardware & supplies	.04 (.09)	−.003 (.02)	−.03	20.6 / 11.8
Outdoor equipment & supplies	.43 (.17)	−.20 (.04)	−.02	4.8 / 3.9
Sporting equipment	.62 (.09)	−.30 (.03)	−.06	6.7 / 5.5
Photography equipment	.22 (.16)	−.41 (.04)	−.21	12.3 / 9.2
Bicycles	.23 (.26)	−.43 (.06)	.10	17.7 /16.5
Pleasure boats	.69 (.12)	.02 (.02)	.09	18.5 / 14.6
Jewelry & Watches	.68 (.07)	−.32 (.04)	−.005	7.7 / 6.6
Luggage	1.17 (.26)	−.55 (.13)	−.07	6.7 / 5.7
Semidurable house furnishings	.67 (.10)	−.33 (.06)	−.12	4.8 / 3.8
Medical goods	.66 (.18)	.14 (.04)	.17	6.0 / 4.8
Toys, dolls & games	.11 (.12)	−.31 (.03)	−.18	42.7 / 28.8

Data: *CPI Commodities and Services Survey*.
Observations are for 3+ months prior to being more permanently unavailable.

*The first markup assumes no productivity growth--yields a monthly growth rate of marginal cost of .215%; the second a productivity pass through of 1/3--marginal cost grows at .07% per month.

Table 4: Cyclicality of Stockout Rates

	(1)	(2)	(3)
Hours (t-1)	−.020 (.034)		
Consumption (t-1)		−.086 (.036)	
Growth in consumption (t-1)			−.046 (.061)
Growth in consumption (t-2)			−.086 (.062)
Cnsumption (t-3)			−.079 (.039)
Adjusted R-squared	−.004	.024	.002
Durbin-Watson stat.	1.78	1.83	1.80
Observations	194	194	194

Dependent variable is the monthly stockout rate for the durables (excluding computers), seasonally adjusted and HP filtered. Hours are monthly hours in durable goods manufacturing (logged), HP filtered. Consumption is the aggregate of real personal consumption expenditures for the durables (logged, excluding computers), HP filtered.

Table 5: Cyclicality of Stockout rates by Durable Good

NIPA Good	Cyclical measure: Aggregate Durable Hours	Cyclical measure: Good's Real Expenditure
Tires	−.02 (.02)	−.02 (.02)
Vehicle accessories & parts	−.01 (.03)	.001 (.03)
Furniture, mattresses & springs	.04 (.06)	−.04 (.04)
Major household appliances	−.19 (.16)	.22 (.13)
Small electric appliances	.13 (.13)	−.05 (.11)
China, glassware, tableware, utensils	−.08 (.08)	−.01 (.07)
Televisions	.10 (.15)	.001 (.10)
Video equipment and media	−.20 (.23)	−.02 (.16)
Audio equipment	.13 (.11)	−.02 (.06)
Audio disks & tapes	−.11 (.11)	−.05 (.08)
Musical instruments	−.06 (.10)	−.02 (.04)
Computers & equipment	−.59 (.34)	−.08 (.13)
Software & accessories	−.60 (.35)	−.02 (.12)
Floor coverings	.09 (.08)	.10 (.05)
Clocks, lamps, & furnishings	−.05 (.10)	.06 (.07)
Window treatments	.07 (.11)	.11 (.09)
Writing equipment	−.53 (.29)	.34 (.23)
Tools, hardware & supplies	.02 (.08)	.08 (.06)
Outdoor equipment & supplies	−.13 (.13)	−.07 (.08)
Sporting equipment	−.05 (.08)	.12 (.06)
Photography equipment	−.35 (.15)	−.13 (.11)
Bicycles	.20 (.20)	−.16 (.16)
Pleasure boats	.15 (.20)	.05 (.04)
Jewelry & Watches	.33 (.26)	−.39 (.17)
Luggage	−.25 (.25)	−.07 (.07)
Semidurable house furnishings	.06 (.08)	−.09 (.08)
Medical goods	.10 (.17)	.10 (.17)
Toys, dolls & games	−.10 (.09)	.003 (.08)

Dependent variable is the monthly stockout rate, seasonally adjusted and HP filtered. Hours are monthly hours in durable goods manufacturing (logged), HP filtered. Consumption is real personal consumption expenditure for the good (logged), HP filtered.

Table 6: Constant Markup Case--Cyclicality of
(Markup) X (Stockout Rate) minus Real Interest Rate

	(1)	(2)	(3)
Hours (t-2)	−.050 (.012)		
Consumption (t-2)		−.043 (.013)	
Growth in consumption (t-2)			.002 (.022)
Growth in consumption (t-3)			.002 (.023)
Cnsumption (t-4)			−.042 (.014)
Adjusted R-squared	.08	.05	.04
Durbin-Watson stat.	1.98	1.85	1.87
Observations	194	194	194

Dependent variable is 10 percent (markup) times the monthly stockout rate minus the reat interest rate, for the durables (excluding computers), seasonally adjusted and HP filtered. Hours are monthly hours in durable goods manufacturing (logged), HP filtered. Consumption is the aggregate of real personal consumption expenditures for the durables (logged, excluding computers), HP filtered.

Table 7: Price Changes After and Before Stockouts

	Dependent Variable				
	(1) Percent Price Change	(2) Freq. of Price Increase	(3) Size of Price Increase	(4) Freq. of Price Decrease	(5) Size of Price Decrease (absolute)
Impact of Stockout On pricing After Stockout	0.19 (.10)	2.03 (.28)	2.80 (.25)	1.01 (.29)	2.23 (.29)
Impact of Stockout On pricing Before Stockout	−1.11 (.08)	−0.78 (.22)	1.46 (.28)	2.90 (.22)	4.01 (.26)

For impact after a stockout the dependent variable is the price change (or how it changes) from four months prior; for impact prior to a stockout it is the change from two months prior. Sample includes only observations not stocking out at observation or at the observation 2 months prior. Regressions include controls for the good, year, and monthly season. It also includes months until permanently unavailable. Results for after stockouts are based on 545,584 observations; results for before are based on 550,767.

Figure 1: Stockout Rates

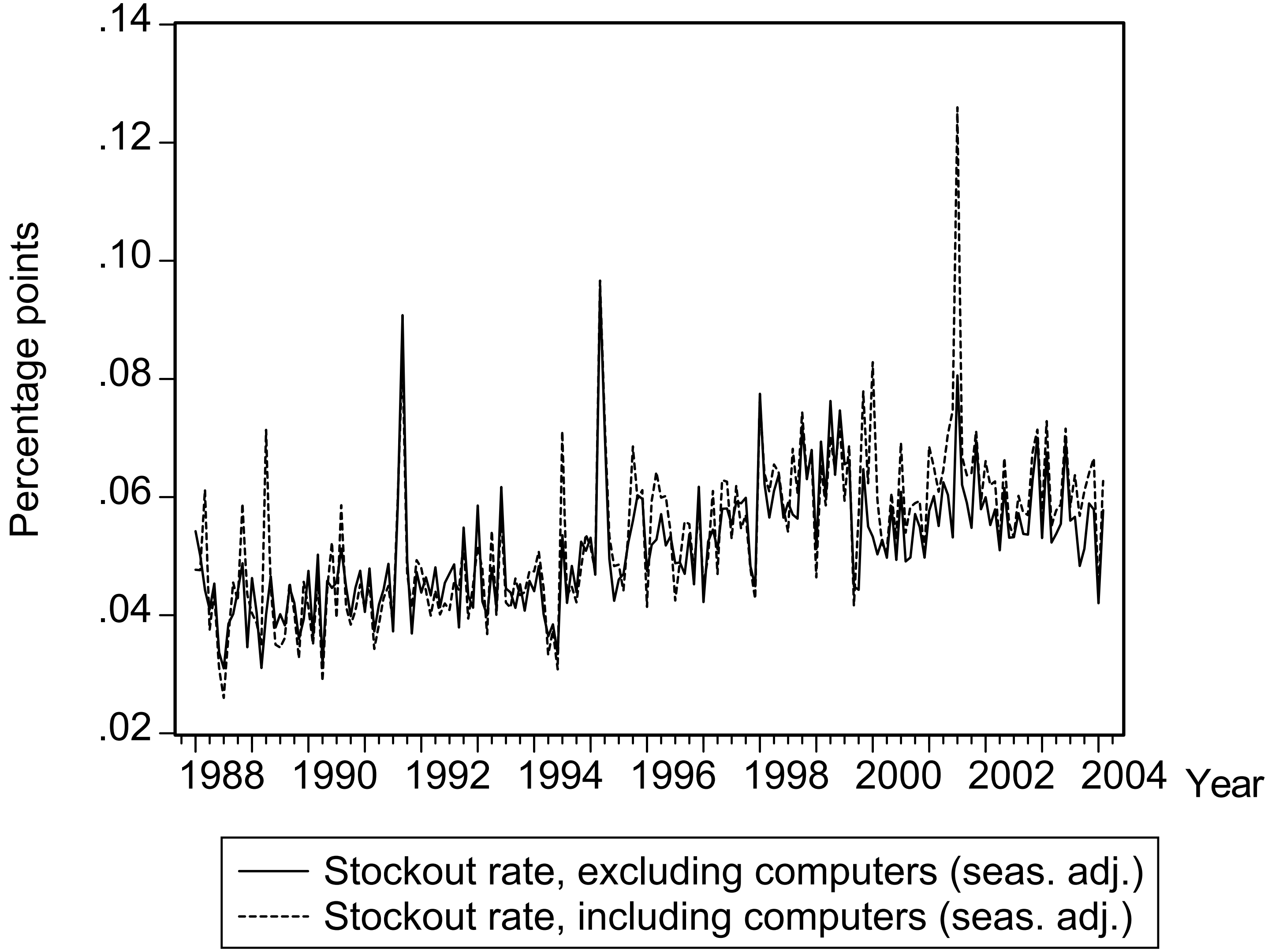


Figure 2: Stockout Rates vs. Hours in Durable Goods Manuf.

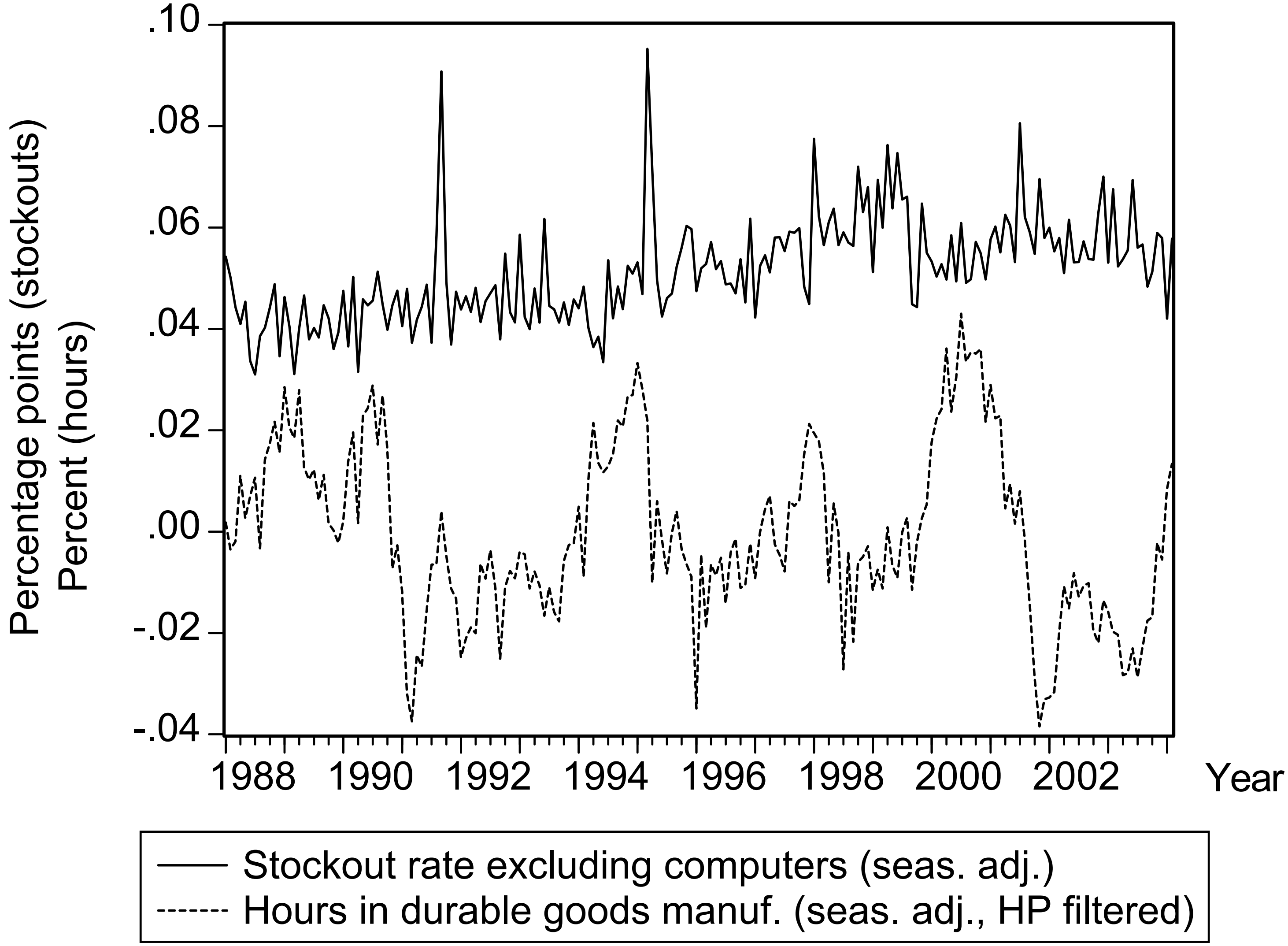


Figure 3: Stockout rates vs. Real Spending on Durables

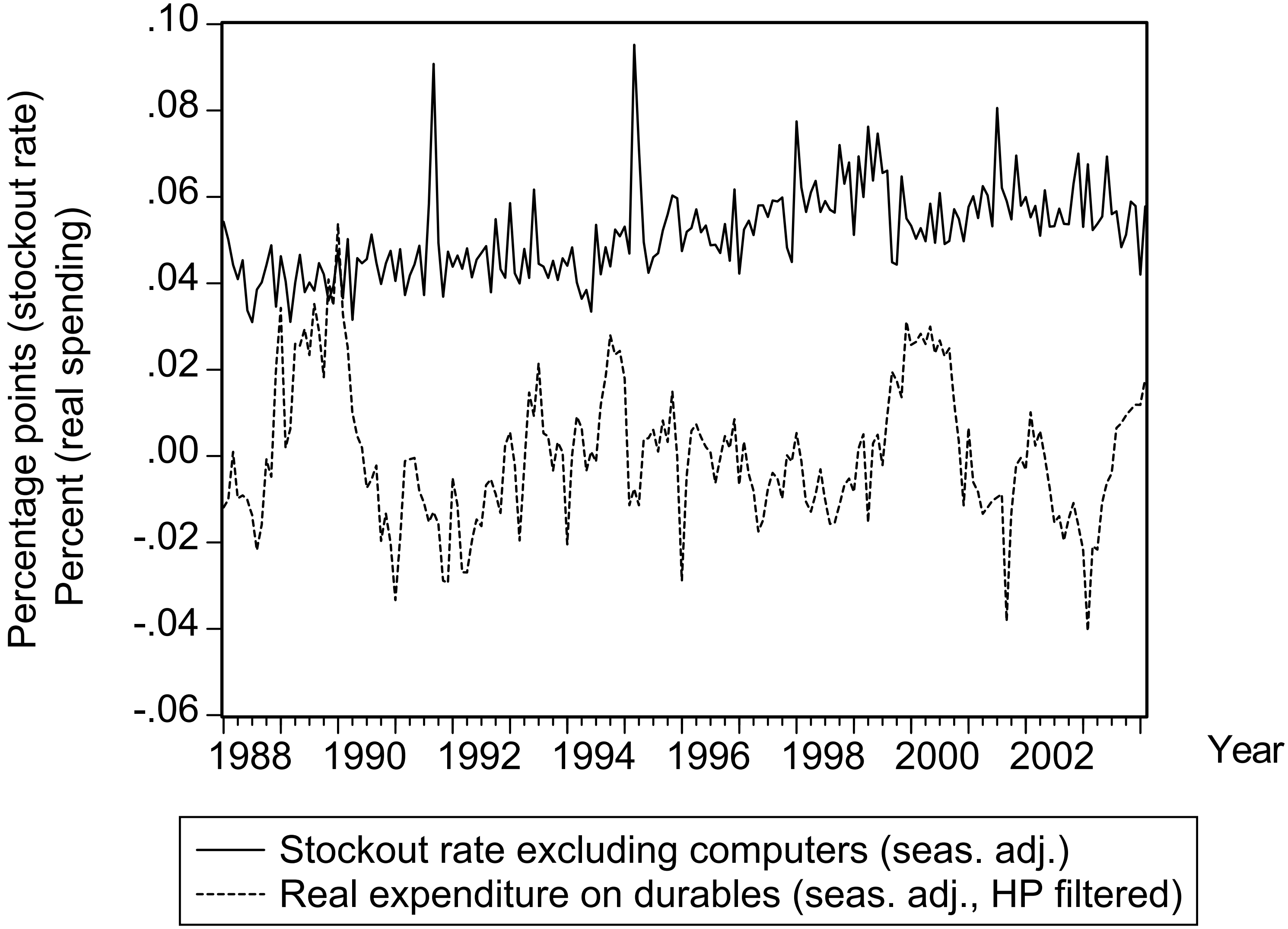


Figure 4: Stockout rates and the Predicted Real Interest Rate for Durable Spending

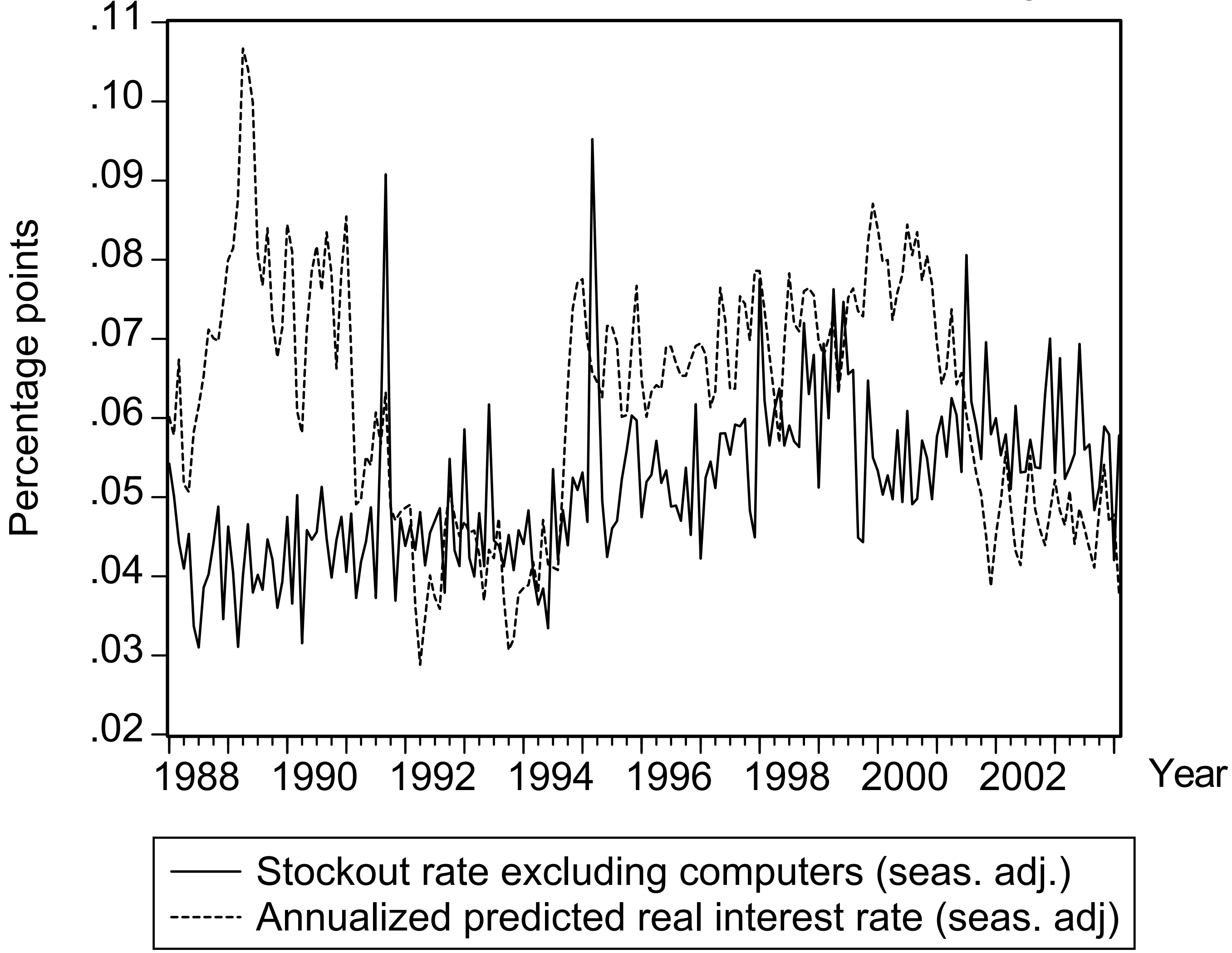
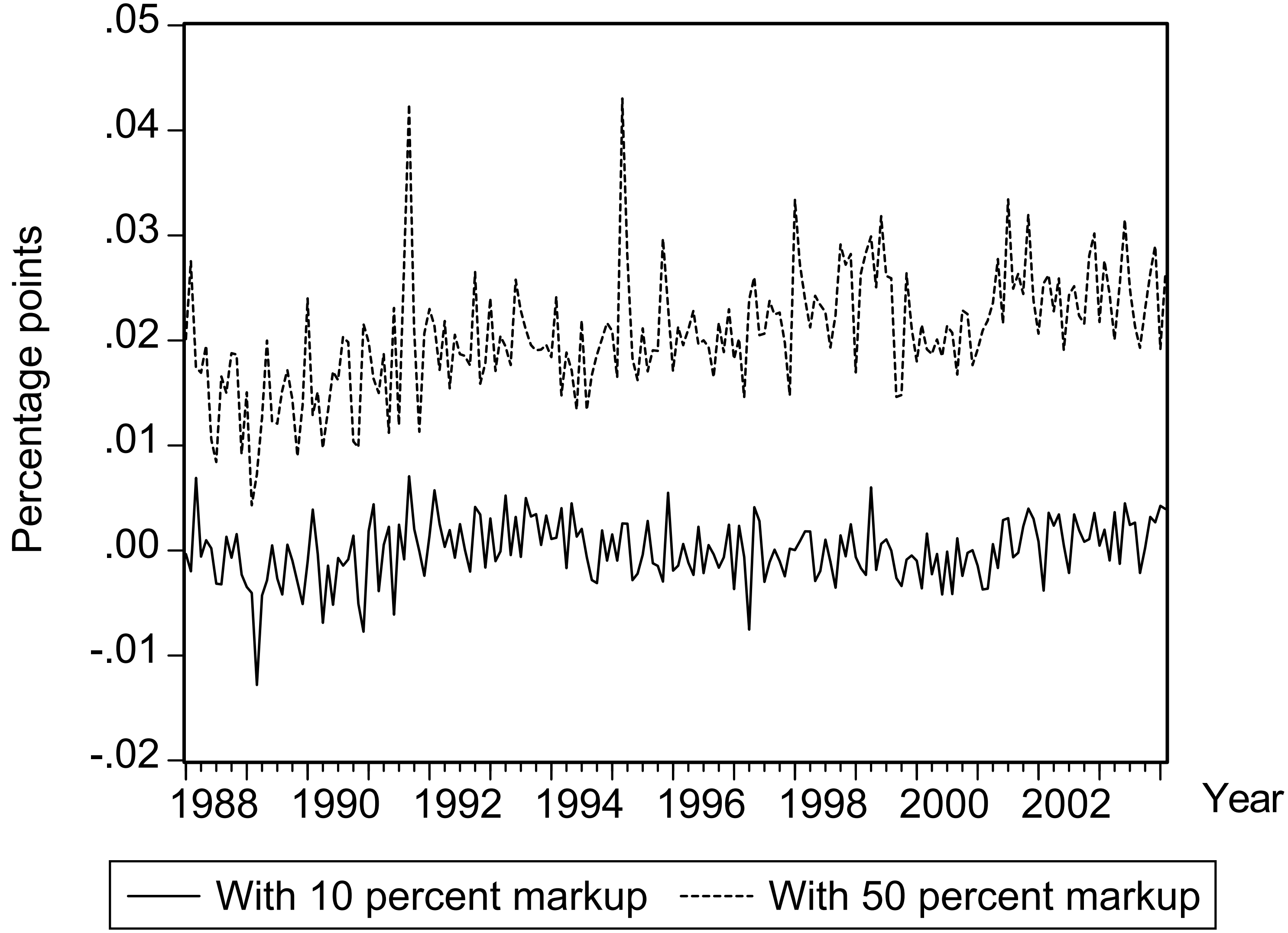


Figure 5: Stockout rate*markup + Ln(Beta*p/p(-1))



Appendix table: Durable Goods Studied

NIPA Good	**Entry level item**	
Tires	Tires	TC011
Vehicle accessories & parts	Vehicle equipment accessories	TC021
	Vehicle audio equipment	RA051A
Furniture, including mattresses & springs	Mattresses & springs	HJ011
	Bedroom furniture	HJ012
	Sofa & slipcover	HJ021
	Living room chairs	HJ022
	Living room tables	HJ023
	Kitchen & dinning room furn	HJ024
	Infant's furniture	HJ031
	Outdoor furniture	HJ032
	Occasional furniture	HJ033
Major household appliances	Refrigerator & home freezer	HK011
	Washers & dryers	HK012
	Stoves	HK013
	Microwaves	HK014
Small electric appliances	Electric pers. care products	GB014
	vacuums	HK021
	small kitchen appliances	HK022
	Other electric appliances	HK023
	Sewing machines	RE021
China, glassware, tableware & utensils	Dishes	HL031
	Flatware	HL032
	Non-electric cookwar	HL041
	Tableware & kitchenware	HL042
Televisions	Televisions	RA011
Video equipment and media	Other video equipment	RA031
	Video cassettes & disks	RA041
	Video games, hardware & software	RE012
Audio equipment	Audio equipment (except vehicle)	RA051B
Audio disks & tapes	Audio disks & tapes	RA061
Musical instruments	Musical instruments & access.	RE031
Computers & equipment	Computers & equipment	EE011
Software	Computer software and access.	EE021
Floor coverings	Floor coverings	HH011
Clocks, lamps, & furnishings	Telephone & equipment	EE041
	infant's equipment	GE013
	lamps & lighting	HL011
	clocks & decorative items	HL012

Appendix Table continued

NIPA Good	Entry level item	ELI
Window treatments	Curtains & drapes	HH021
	window coverings	HH022
Writing equipment	Calculators, typewriters, etc.	EE042
Tools, hardware & supplies	Paint, wallpaper, tools & supplies	HM011
	Power tools	HM012
	Misc. hardware	HM013
	Non-powered hand tools	HM014
	Building supplies & hardware equip	HM090
Outdoor equipment & supplies	Lawn, garden & outdoor equipment	HM021
Sporting equipment	General sports equipment	RC2122
	Hunting, fishing & camping equipment	RC023
Photography equipment	Photography equipment	RD012
Bicycles	Bicycles	RC013
Pleasure boats	Outboard motors & powered sports equip.	RC011
	Boats (not powered) & trailers	RC012
Jewelry & Watches	Watches	AG011
	Jewelry	AG021
Luggage	Luggage	GE012
Semidurable house furnishings	Bathroom linens	HH031
	bedroom linens	HH032
	Kitchen linens	HH033
Medical goods	Medical equipment for general use	MB022
	Supportive & convalescent equipment	MB023
Toys, dolls & games	Toys, games & playground equipment	RE011

Data: *CPI Commodities and Services Survey*.

References

Abraham, Katherine and John Haltiwanger (1995), "Real Wages and the Business Cycle," *Journal of Economic Literature*, 33, 1215-1264.

Aguirregabiria, Victor (2003), "Strategic Stockouts in Supermarkets," manuscript, Boston University.

Bils, Mark and James A. Kahn (2000), "What Inventory Behavior Tells Us about Business Cycles?" *American Economic Review* 90, 458-481.

Campo, K., E. Gijsbrechts, and P. Nisol (2003), "The Impact of Retailer Stockouts on Whether, How Much, and What to Buy," *International Journal of Research in Marketing* 20, 273-286.

Christiano, Lawrence, Martin Eichenbaum, and Charles Evans (2003), "Nominal Rigidities and the Effects of a Shock to Monetary Policy," manuscript, Northwestern University.

Emmelhainz, M., J. Stock, and L. Emmelhainz (1991), "Consumer Responses to Retail Stockouts," *Journal of Retailing* 67, 138-147.

Fitzsimons, G. (2000), "Consumer Response to Stockouts," *Journal of Consumer Research* 27, 249-266.

Galeotti, Marzio, Louis J. Maccini, and Fabio Schiantarelli (2002), "Inventories, Employment, and Hours," manuscript, Johns Hopkins University.

Gali, Jordi, Mark Gertler, Lopez-Salido (2002), "Markups, Gaps, and the Welfare Costs of Business Cycle Fluctuations," NBER Working Paper 8850.

Goodfriend, Marvin and Robert G. King (1997), "The New Keynsian Neoclassical Synthesis and the Role of Monetary Policy," *NBER Macroeconomics Annual* 12, 233-283.

Hall, Robert E. (1997), "Macroeconomic Fluctuations and the Allocation of Time," *Journal of Labor Economics* 15, S223-S250.

Kahn, James A. (1987), “Inventories and the Volatility of Production.” *American Economic Review*, 77, 667-79.

Kahn, James A. (1992), “Why is Production more Volatile than Sales? Theory and Evidence on the Stockout-Avoidance Motive for Inventory Holding.” *Quarterly Journal of Economics*, 107, 481-510.

Kashyap, Anil and David W. Wilcox (1993), "Production and Inventory Control at the General Motors Corporation in the 1920's and 1930's," *American Economic Review*, 83, 383-401.

Krane, Spencer D. and Steven N. Braun (1991), "Production Smoothing Evidence from Physical Product Data." *Journal of Political Economy*, 99, 558-581.

Pindyck, Robert S. (1994), "Inventories and the Short-Run Dynamics of Commodity Prices," *Rand Journal of Economics*, 25, 141-159.

Ramey, Valerie A. (1991), "Non-Convex Costs and the Behavior of Inventories." *Journal of Political Economy*, 99, 306-334.

Rotemberg, Julio J. and Michael Woodford (1999), "The Cyclical Behavior of Prices and Costs." In *Handbook of Macroeconomics*, North-Holland: Elsevier Science Publishers B.V., North Holland Press.

Rotemberg, Julio J. and Lawrence H. Summers (1990), "Inflexible Prices and Procyclical Productivity," *Quarterly Journal of Economics*, 105, 851-874.

Sbordone, Argia, M. (2001), "An Optimizing Model of Wage and Price Dynamics," manuscript, Rutgers University.

Taylor, John B. (1999), "Staggered Price and Wage Setting in Macroeconomics" chapter 15 in *Handbook of Macroeconomics*, Volume 1B, John B. Taylor and Michael Woodford, eds., Elsevier, New York.

Thurlow, Peter H. (1993), *Essays on the Macroeconomic Implications of Inventory Behavior*. Ph.D. dissertation, University of Toronto.

U.S. Department of Labor (1997), *BLS Handbook of Methods*, Bulletin 2490, U.S. Government Printing Office.

West, Kenneth D. (1990), "The Sources of Fluctuations in Aggregate Inventories and GNP." *Quarterly Journal of Economics*, 105, 939-971.