Price Movements over the Business Cycle in U.S. Manufacturing Industries[*]

by

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and

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Abstract: This paper develops and tests implications of an oligopoly pricing model. The model involves capacity investments that are made before demand is revealed and pricing decisions that are made after demand is known. The model predicts that during a demand expansion the short run competitive price is a pure strategy Nash equilibrium, but in a recession firms set prices above the competitive price. Thus, price markups over the competitive price are countercyclical. Prices set during a recession are more variable than prices set during expansionary periods, because firms use mixed strategies for prices in recessions. This model is confronted with data from U.S. manufacturing industries. The empirical analysis utilizes a time series switching regime filter to test the unique predictions of the model, namely that (1) price changes are more variable in recessions than in expansions and (2) the form of the distribution of price changes differs between recessionary and expansionary regimes. Fourteen out of fifteen industries have fluctuations consistent with this oligopoly pricing model. The data is also analyzed to compare the predictions of this model with those of an optimal collusion model.

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[*] Wilson acknowledges research support from the John M. Olin Foundation and the National Science Foundation (Grant No. SBR-9507526). This paper is an extension of Chapter 4 of Wilson's Ph.D. dissertation. Doc Ghose, Mark Walker, and John Wooders provided helpful suggestions. This paper has also benefited from comments by seminar participants at the University of Arizona, the University of Houston, Johns Hopkins University, the University of Kansas, the University of Toronto, and Virginia Polytechnic Institute and State University. This work represents the opinions of the authors and is not intended to represent the position of the Federal Trade Commission or any individual Commissioner.

The adjustment of product market prices to changes in demand plays an important role in business cycle fluctuations. A greater degree of price inflexibility in response to market demand changes may lead to larger swings in real output and employment when an economy is subjected to aggregate demand shocks. Indeed, Rotemberg (1982) finds evidence of sluggish price adjustment in aggregate U.S. price data.

Recent research on product market price adjustment has focused on firms' market power and how this power may be exercised differentially over the business cycle. For example, studies by Greenwald et al. (1984), Gottfries (1991), Klemperer (1995), and Chevalier and Scharfstein (1996) have emphasized the role of capital-market imperfections. When capital-market imperfections exist, the incentives for firms to make investments may be reduced because firms may not reap the profits associated with the investment. One form of investment is a low price that builds a firm's market share by attracting more customers in the future. During a recession, firms may raise prices, forgoing any attempt to raise future market share, because the probability of default is high. Chevalier and Scharfstein (1996) find support for this hypothesis in data drawn from the supermarket industry. Another strand of the literature has emphasized the role of collusion. Rotemberg and Saloner (1986), Rotemberg and Woodford (1991, 1992) and Bagwell and Staiger (1997) show that a firm participating in a collusive group may have more incentive to defect during a boom period, because the short term gains from defection are relatively large. Thus, an optimal collusive mechanism may involve lower prices (or markups over marginal cost) during booms than during recessions, in order to eliminate the incentive to defect.[1]

We propose an alternative model of oligopoly pricing that has implications for variations

[1] If marginal cost is increasing with output then optimal collusion may involve countercyclical markups over marginal cost coupled with procyclical price levels. Bagwell and Staiger (1997) show that the structure of an optimal collusive mechanism is sensitive to the autocorrelation of demand shocks. Positively correlated demand

in prices and industry efficiency over the business cycle. We refer to this as a non-collusive oligopoly model to distinguish it from collusive theories of oligopoly behavior over the business cycle. Our model emphasizes the role of long run production capacity investments that must be made before demand conditions are known. After capacity investments are made, firms learn about the level of product demand and choose prices. The pricing incentives for firms differ depending on the level of demand. If demand is high, then the short run competitive (market clearing) price is a pure strategy Nash equilibrium. However, if demand is low, then capacity constrained firms have an incentive to deviate from the short run competitive price. The typical result is that firms adopt mixed strategies for prices that involve a markup over the short run competitive price and that generate excess production capacity.

Our non-collusive oligopoly model predicts that output prices are procyclical, as do many other theories. The key prediction that distinguishes the model from other theories is that output prices are predicted to have greater variance during low demand periods than during high demand periods. Two other implications of our non-collusive oligopoly model are noteworthy. First, price adjustments are sluggish in the downward direction, relative to perfectly competitive prices. If demand changes from high to low then oligopoly firms reduce prices by an amount less than the change in the competitive price, since oligopoly firms charge a markup over the short run competitive price when demand is low. A second (and related) implication is that existing capacity is utilized efficiently when demand is high but may be utilized inefficiently when demand is low. Oligopoly price markups above the short run competitive price can lead to less output and employment than is efficient when demand is low.

In Section I we formalize the idea that ex ante capacity investments coupled with ex post price setting lead to price variation over the business cycle. We begin with a formal two-stage

shocks can yield procyclical markups over marginal cost and procyclical price levels.

duopoly model of investment and pricing in which product demand may be either high or low. This model can be viewed as an extension of Kreps and Scheinkman (1983) to allow for demand uncertainty. As long as the difference in demand between high and low levels is limited, equilibrium prices conditional on low demand involve a markup over the short run competitive price and positive variance. Later in Section I, we embed the two-stage model in a dynamic business cycle setting in which demand alternates stochastically between fast-growth (boom) phases and slow-growth (recession) phases. This formulation provides the structure for our empirical tests. This specification also corresponds to Bagwell and Staiger's (1997) specification of demand changes in their analysis of optimal collusive mechanisms.

The empirical analysis in section II does not attempt to estimate price markups directly.[2] Instead, the analysis investigates an implication of our non-collusive oligopoly model for observed prices. The dynamic version of the model predicts that price changes are more variable during recessions than during booms, because firms employ mixed strategies during recessions. Another prediction resulting from the mixed strategy equilibrium is that the distribution of price changes differs in recessions. These implications are tested using a type of time series switching regime filter employed by Hamilton (1989). We examine seventeen manufacturing industries at the two- and three-digit Standard Industrial Classification (SIC) level. A separate time series model is estimated for each industry. Fourteen of these industries have substantially higher price change variances and distinctly different forms of the price change distribution when production is in a recessionary state.

Before beginning our analysis, we briefly review the relevant empirical evidence on price markups. Domowitz, Hubbard, and Petersen (1987) examine the empirical evidence on cyclical responses of prices and price-cost margins. With a panel data set of industries at the four-digit

[2] The estimation of price-cost margins or of markups over a competitive price involves potential measurement

SIC level spanning 1958-1981, they find that more concentrated industries have more procyclical margins. As they note, these estimates may be biased upward (downward) if marginal cost is greater (less) than measured average variable cost. Consistent with the Rotemberg and Saloner predictions, Domowitz et al. further find that industries with high price-cost margins have more countercyclical price movements. However, Domowitz et al. use industry-level changes in capacity utilization as a proxy for business cycle movements. Low capacity utilization at the industry level may simply be a result of high prices, rather than the result of a downward shift in demand. Bresnahan (1989) also points out the limitations of cross-industry comparisons of competition when assessing cyclical variations of margins and prices.

To avoid the problems of using accounting data for estimating the price-cost margin, Domowitz (1992) takes an approach that examines total factor productivity. He adjusts the Solow residual to allow firms to price above marginal cost and then permits the price-cost margin to vary with the level of aggregate demand as measured by capacity utilization in manufacturing. Domowitz's point estimates indicate that there is a negative correlation between the margin and aggregate demand movements; however, the standard errors are large enough so that the null hypothesis of acyclicality cannot be rejected.

Bresnahan and Suslow's (1989) study of the aluminum industry does not reveal any evidence of oligopoly market power. They develop an econometric model of short run supply, capacity constraints, and long-lived capital. Employing a switching regression model, they find evidence of two regimes in their reduced form quantity-produced and quantity-shipped equations. The implication is that in the high demand regime, prices are determined by the vertical portion of a supply curve when production is constrained at capacity. Output is unconstrained in the second regime, output falls well short of capacity, and prices are determined

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problems, as explained below.

by linear average variable costs. The aluminum industry is part of one of the industry groups considered in our empirical analysis. Our empirical results for this industry are largely consistent with theirs; we find no evidence of price markups above the competitive price in recessions for this industry. However, this industry is the exception rather than the rule among the industries that we examine.

Wilson (1997) reports evidence from laboratory experiments on oligopoly pricing. The experiments are similar to Davis and Holt's (1994) posted offer pricing experiments except that Wilson considers the effects of a demand shift rather than the effects of a supply/capacity change. The results are broadly consistent with the model's predictions. When demand is high, prices are near the short run competitive level. When demand is low, prices remain above the short run competitive level and prices are more variable than when demand is high. When demand is low prices fail to conform precisely to the equilibrium mixed strategy predictions. Prices appear to follow a disequilibrium process similar to an Edgeworth cycle process.

I. The Theoretical Model

We develop a duopoly model of capacity investment and pricing. The level of demand is uncertain when firms make investment decisions but is known before firms make pricing decisions. The initial formulation involves a simple two-stage game with a step demand function.[3] Later in this section we embed the two-stage game in a dynamic, business cycle setting that provides the basis for the econometric analysis.

Two-Stage Model

We assume there are two levels of demand, "low" and "high". Let $a \in \{\underline{a}, \overline{a}\}$ represent the total mass or number of customers, with $0 < \underline{a} < \overline{a}$. The probability that demand is low is

[3] Reynolds and Wilson (1997) analyze more general models of this type, including formulations with a downward

$\theta \in (0,1)$. All consumers are assumed to have a common value, v, for one unit of the product; the market demand is then a step function with height v and length a.

The marginal cost of capacity in the first stage is c. Firm one chooses capacity x and firm two, capacity y. The marginal cost of production is constant in stage 2, and is normalized to zero. The parameter v can be interpreted as the value of the good minus the short run marginal production cost. We assume that both firms know v and c, with $v > c > 0$.

The level of demand is observed before firms set prices in stage two. A subgame in stage two is defined by the triple, (x,y,a). There are three cases to consider. First, suppose that $x+y \le a$. This is region A in the graph of capacity pairs in Figure 1. If the capacities are in region A, then a price equal to v is a dominant strategy for each firm. Note that v is also the short run competitive price when capacities are in A.[4] A firm's subgame payoff (revenue) is simply v times its capacity. Second, suppose that $x \ge a$ and $y \ge a$. Each firm has enough capacity to serve the market by itself and the pricing subgame corresponds to a situation of Bertrand price competition. This is region B in Figure 1. The unique subgame Nash equilibrium (NE) has both firms setting price equal to zero (the short run competitive price) and each firm earns zero in the subgame. The final case is represented by region C in Figure 1. Total capacity exceeds the size of the market, but at least one firm is too small to serve all consumers by itself. In this case there is no pure strategy equilibrium for the pricing subgame (except for the trivial case in which one firm's capacity is zero). A subgame Nash equilibrium involves mixed strategies for prices. Reynolds and Wilson (1997) derive equilibrium price distributions and expected revenues for this case. Equilibrium prices exceed the short run competitive price of zero.

The expected revenue for firm one in a subgame equilibrium is given by the following

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sloping demand. However, the simple formulation of the present paper yields the principal empirical implications that we search for in the data.

[4] If total capacity is less than a then v is the unique competitive price. If total capacity equals a then v is the upper

function (see Reynolds and Wilson (1997)):

$$r(x,y,a)=\begin{cases} vx & (x,y)\in A \\ v(a-x)x/y & (x,y)\in C,\ x\le y<a \\ v(a-x)x/a & (x,y)\in C,\ x<a\le y \\ v(a-y) & (x,y)\in C,\ x>y \\ 0 & (x,y)\in B \end{cases}$$

Expected revenue for firm two is given by $r(y,x,a)$. The function $r(\cdot)$ is continuous in each of its arguments.

In stage one firms choose capacities. The level of demand is uncertain in stage one. Expected profits as a function of capacities are

$$\pi(x,y)=\theta r(x,y,\underline{a})+(1-\theta)r(x,y,\overline{a})-cx$$

for firm one and $\pi(y,x)$ for firm two.

The following two assumptions are utilized.

Assumption A1: $(1-\theta)v>c$

Assumption A2: $\frac{3}{2}\underline{a}>\overline{a}$

A1 is a condition that makes it attractive for firms to invest so that total capacity is sufficient to serve all consumers when demand is high. Without *A1*, firms would not (collectively) invest in capacity beyond $\underline{a}$, and excess capacity would never emerge. *A2* limits the difference in demand levels; high demand is no more than 50 percent above low demand. In the absence of a condition like *A2*, an equilibrium may involve a Bertrand-type outcome with prices equal to short run marginal cost when demand is low.

Under *A1* and *A2* a pure strategy equilibrium in capacity choices exists. The derivations appear in Appendix *A*. There are two principal types of reaction function configurations. If $\theta\le\overline{a}(1-c/v)/(3\overline{a}-2\underline{a})$, then reaction functions are as in Figure 2A. There is a continuum of

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bound on the interval of competitive prices.

equilibria, which includes a symmetric capacity pair. If $\theta > \overline{a}(1 - c/v)/(3\overline{a} - 2\underline{a})$, then reaction functions are as in Figure 2B. Again, there is a continuum of equilibria. However, the equilibrium set does not include a symmetric capacity pair because reaction functions have a discontinuity involving a "jump" across the 45 degree line.

The main results may be summarized as follows.[5] There is a continuum of equilibria. Equilibrium capacities sum to $\overline{a}$, the level of high demand. If demand is high, then in stage two both firms set price v, which is the upper bound of the set of short run market clearing prices. There is no excess capacity. If demand is low, then in stage two both firms adopt mixed strategies for prices, with prices above the short run market clearing price of zero. Prices have positive variance and excess capacity emerges. An illustration of equilibrium price distributions for a low demand realization is provided in Figure 3. The figure illustrates the skewness of pricing distributions that is a feature of equilibrium mixed strategies in Bertrand-Edgeworth models.

We use the term *price markup* to indicate the difference between a firm's price and the (maximum) short run competitive price.[6] Equilibrium prices are procyclical while equilibrium price markups are countercyclical in the simple two-stage game.

The predicted variation of prices when demand is low may seem to be at odds with the notion of price rigidity that was noted at the beginning of the paper. After all, New Keynesian's explain that the difficulties posed by imperfect competition are due to inflexible prices rather than to excessive price variation. In spite of this apparent contradiction, there is in fact a form of

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[5] The two-stage model is formulated as a duopoly. However, the basic results on markups and price variability continue to hold for markets with more than two firms, as long as the market does not become too competitive. For example, suppose that there are $n \geq 2$ equal sized firms, with total capacity equal to $\overline{a}$. If $n + 1 < \overline{a}/(\overline{a} - \underline{a})$, then when demand is low, equilibrium prices are draws from a mixed strategy distribution; prices involve a positive markup over short run marginal cost and prices have positive variance.

[6] Our usage of the term markup may be somewhat unconventional. The markup term is often used to indicate the difference between price and short run marginal cost. In our setting, short run marginal cost is not defined for

price rigidity in the our model. The rigidity can be understood by noting that when demand changes from high to low, equilibrium prices decrease by less than short run competitive prices.

A Dynamic, Business Cycle Formulation

In an analysis of business cycle fluctuations, Hamilton (1989) formulates a model of the growth rate of aggregate U.S. output. This formulation involves an unobserved state variable that indicates whether the economy is in a low-growth or a high-growth state, and a Markov process governing transitions between states. Hamilton develops an estimation procedure for this model and finds that it provides a good characterization of aggregate business cycle fluctuations.[7] This type of two-state growth process is also utilized in Bagwell and Staiger's (1997) theoretical analysis of collusive pricing over the business cycle.

We adapt Hamilton's business cycle model to formulate a model of demand fluctuations in a single market. Let a_t denote the market size in period t. s_t is the "state" at date t and takes on the value of one or two. The evolution of the state variable is governed by a Markov chain process with, $p_{ij} = \text{Prob}[s_t = j | s_{t-1} = i]$, $i, j \in \{1,2\}$. The size of the market follows a state dependent trend $a_{t+1} = \tau_{s_{t+1}} a_t$ where $\tau_1 > \tau_2 > 0$. In percentage terms, demand growth between t and $t+1$ is, $ln(a_{t+1}) - ln(a_t) = ln(\tau_{s_{t+1}})$.

There are two stages within each time period. Capacities are chosen in the first stage of each period. In stage one of period t, a_{t-1} and s_{t-1} are known, but a_t is unknown. So, if $s_{t-1} = i$, then p_{i2} is the probability of low growth (or contraction if $\tau_2 < 1$) from t-1 to t. Firms choose prices in stage two of period t after observing the level of demand, a_t. Another interpretation is that firms are producing to a stock each period, but it is after production occurs that the firms

output equal to capacity. We use the short run competitive price as a benchmark instead of marginal cost.

[7] The business cycle dates from Hamilton's filter closely correspond to the traditional NBER dates. It is also worth noting that the unobservable state is only one of many influences on the growth rate so that output could be falling even though the economy is in the "high" growth rate state.

learn the actual level of demand and choose prices. For industries with large irreversible capacity investments (e.g., chemicals), this must be the interpretation.

We add a feature to the model to allow for price variations due to variations in production costs. Let b_t be the real short run marginal cost of production in t, and let r_t be consumers' real reservation price in t. Assume that b_t is an i.i.d. random variable with $E(b_t) = \bar{b} > 0$ and $Var(b_t) = \sigma_b^2$. Furthermore, we assume that $r_t = b_t + v$; i.e., reservation prices and short run marginal costs are perfectly correlated. Firms observe r_t and b_t after capacities are set in t and before prices are set in t. Variations in r_t and b_t do not influence firms' expected revenue associated with capacity investments, since v is constant.

The marginal cost of capacity investment is also permitted to be time dependent through the state variable, s_t. Let $c(s_{t-1})$ be the marginal cost of capacity in t. Assume that $0 < c(1) \leq c(2) < v$ so that the marginal cost of capacity following slow growth periods is less than or equal to marginal capacity cost following high growth periods. The following two assumptions are counterparts to *A1* and *A2*.

Assumption B1: $(1 - p_{i2})v > c(i)$, $i = 1,2$

Assumption B2: $\frac{3}{2}\tau_2 > \tau_1$

Consider first the two-stage game for a single period t, given any a_{t-1} and s_{t-1}. Under assumptions *B1* and *B2* an equilibrium pair of capacities exists for this two-stage game. Equilibrium capacities in period t sum to $\tau_1 a_{t-1}$. The set of equilibrium capacities may differ depending on the value of state s_{t-1}, since the probability of low demand and the marginal cost of capacity are both permitted to depend on s_{t-1}. If demand is high then both firms set a price equal to r_t, the real reservation price. If demand is low, then firms adopt mixed strategies for prices over a support contained in $(b_t, r_t]$.

Now consider the infinite horizon game beginning in period one, given initial conditions, (a_0, s_0). Let δ be a common discount factor, where we assume that $\tau_1 \delta < 1$, so that payoffs are bounded. We focus on equilibria that have two features: (1) firms use strategies that constitute an equilibrium for the two-stage game in each period t, conditional on (a_{t-1}, s_{t-1}), and (2) the market shares of capacities are the same whenever the previous period state is the same. Equilibria with these features yield a stationary Markov process for price and quantity changes. The next step of the analysis is to characterize such a process.

Suppose that $(s_{t-1}, s_t) = (1,2)$; i.e., there is high growth in t-1 and low growth in t. Then in period t firms utilize mixed strategy distributions of prices. As long as $s_{t-1} = 1$, this distribution is the same, regardless of the value of a_{t-1}, given the features of the equilibrium we consider. Let m_{1t} be a random variable representing the average of the two firms' prices less marginal production cost, based on their mixed strategies, with $m_{1t} \in (0, v]$, $E(m_{1t}) = \overline{m}_1 < v$, and $Var(m_{1t}) = \sigma^2_{m_1}$.

Suppose instead that $(s_{t-1}, s_t) = (2,2)$; i.e., there is low growth in periods t-1 and t. Firms utilize mixed strategy distributions of prices and, as long as $s_{t-1} = 2$, this distribution is the same, regardless of the value of a_{t-1}. Let m_{2t} be a random variable representing the average of the two firms' prices less marginal production cost, based on their mixed strategies, with $m_{2t} \in (0, v]$, $E(m_{2t}) = \overline{m}_2 < v$, and $Var(m_{2t}) = \sigma^2_{m_2}$.

With two states the model makes four predictions for price and quantity changes. Let p_t and q_t represent the percentage change in prices and quantity, respectively. The results are derived in Appendix B and summarized in Table I. The testable implications of the model are twofold. First, during recessions $(s_t = 2)$ the model predicts that changes in price will have a larger variance than during booms. Second, the form of the distribution of price changes will be different in recessions than in booms. For example, suppose that b_t is normally distributed. Then prices in booms are normally distributed, while prices in recessions consist of a normally distributed marginal cost component and a non-normally distributed price markup component. This generates price changes in recessions that have a distribution that is not Gaussian.

Table I
Model Predictions*

	s_t = 1	s_t = 2
s_{t-1} = 1	$E(p_t)=0$ $E(q_t)=ln\tau_1$ $Var(p_t)=2\phi_0\sigma_b^2$ $Var(q_t)=0$	$E(p_t)=ln\left(\dfrac{\bar{b}+\bar{m}_1}{\bar{b}+v}\right)<0$ $E(q_t)=ln\tau_2$ $Var(p_t)=(\phi_0+\phi_1)\sigma_b^2+\phi_1\sigma_{m_1}^2$ $Var(q_t)=0$
s_{t-1} = 2	$E(p_t)=ln\left(\dfrac{\bar{b}+v}{\bar{b}+\bar{m}_2}\right)>0$ $E(q_t)=ln\tau_1$ $Var(p_t)=(\phi_0+\phi_2)\sigma_b^2+\phi_2\sigma_{m_2}^2$ $Var(q_t)=0$	$E(p_t)=0$ $E(q_t)=ln\tau_2$ $Var(p_t)=2\phi_2(\sigma_b^2+\sigma_{m_2}^2)$ $Var(q_t)=0$

* $\phi_0 \equiv \dfrac{1}{(\bar{b}+v)^2}, \phi_1 \equiv \dfrac{1}{(\bar{b}+\bar{m}_1)^2}, \phi_2 \equiv \dfrac{1}{(\bar{b}+\bar{m}_2)^2}, \phi_1 > \phi_0, \phi_2 > \phi_0$

II. Estimation Approach, Data and Empirical Analysis

The business cycle formulation of the previous section generates a specific time series model of price and quantity changes. However, some features of the model are too restrictive. For example, the predicted variance of quantity changes is zero in each state; only two different quantity-change amounts are predicted to appear. In what follows we specify an empirical model that is more general than what is laid out in Table I. We allow a nonzero covariance between price and quantity changes. As we will discuss later, this permits a test of a prediction in an optimal collusive model. More importantly, a positive variance for quantity change is permitted in each state. The state variable is not observed, so that the observed path of price and quantity changes must be used to make inferences about the values of the state variable (as with the Kalman filter). The unobserved state is assumed to be one of two growth rates, "high" or "low," and the probabilistic switch from one state to another is assumed to follow a Markov process. This approach to the issue of cyclical pricing is appealing because the data will determine when an industry switches regimes and whether relative price changes are more variable or not in recessions.

Time Series Model

The model we use is of the type formulated by Engel and Hamilton (1990) to test the hypothesis of uncovered interest parity. Let $\mathbf{y}_t = [q_t, p_t]'$ be a two-dimensional vector at date t where q_t is the percentage change in production and p_t is the percentage change in price for a particular industry. There is an unobservable variable, s_t, which characterizes the "state" at date t and takes on the value of one or two. In Engel and Hamilton (1990), $\mathbf{y}_t$ is drawn from one bivariate distribution if the state in t is equal to one and a second bivariate distribution if the state in t is equal to two. Our setting is somewhat more complex, in that we have predictions on the distribution governing $\mathbf{y}_t$ draws conditional on both the current and the prior state (recall Table I). Depending on the current and prior states, the contemporaneous changes in the growth rates of production and real prices are drawn from a $N(\mu_{s_{t-1},s_t}\ ,\ \Omega_{s_{t-1},s_t})$ distribution. Thus, there are four different bivariate distributions governing $\mathbf{y}_t$ draws, since the pair (s_{t-1}, s_t) can take on four different values.

The state variable follows the Markov chain process specified in Section I. Only through s_{t-1} do past realizations of y and s affect the unobservable state variable. Note that the draws of

$\mathbf{y}_t$ are *not* independent draws from a mixture of normal distributions. The inferred probability that $\mathbf{y}_t$ is drawn from one distribution depends on all the realizations of $\mathbf{y}$ prior to time t. This approach differs from the Bresnahan and Suslow (1989) switching regime regression in that all prior information is used to infer the current probability that $\mathbf{y}_t$ is drawn from a particular distribution.

The bivariate model of stochastic segmented trends permits a wide variety of behavior for the series. First, the industry mean production growth rates may pick up slow or fast growth rates of production for an industry. The production growth rates could also be the same in both regimes, or one state may reflect recessionary periods and the other expansionary periods. Likewise, these combinations are possible for the contemporaneous real price regimes.

The model described above is the basis for estimation of a parameter vector, $\theta = (\mu_{11}, \mu_{12}, \mu_{21}, \mu_{22}, \Omega_{11}, \Omega_{12}, \Omega_{21}, \Omega_{22}, p_{11}, p_{22})'$. This vector has 22 parameters. The sample log likelihood function, $ln\, p(\mathbf{y}_T, \mathbf{y}_{T-1}, \ldots, \mathbf{y}_1; \theta)$, which is to be maximized with respect to the unknown parameters of θ, can be constructed from the conditional likelihood of $\mathbf{y}_t$. The conditional likelihood of $\mathbf{y}_t$, $p(\mathbf{y}_t | \mathbf{y}_{t-1}, \ldots, \mathbf{y}_1; \theta)$, is a byproduct of Hamilton's (1989) filtering algorithm. We can infer the probability that $\mathbf{y}_t$ was drawn from a particular state s_t based on all information available at time t: $p(s_t | \mathbf{y}_1, \ldots, \mathbf{y}_t; \theta)$. Furthermore, a full sample smoother can be used to draw inference on the regime at date t using all the information available *ex post*: $p(s_t | \mathbf{y}_1, \ldots, \mathbf{y}_T; \theta)$.[8, 9]

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[8] Two issues arise when attempting to find the maximum likelihood estimate $\hat{\theta}$. Both involve the process of finding the global maximum of the sample log likelihood function. From the filter we can determine the sample log likelihood function as the sum of the conditional log likelihoods:

$ln\, p(y_T, y_{T-1}, \ldots, y_1) = \sum_{t=1}^{T} ln\, p(y_t | y_{t-1}, \ldots, y_1)$. As in Hamilton (1989) the sample log likelihood can be maximized using numeric hill-climbing methods, but systems with a large number of parameters (e.g., twenty-two) often have many local maxima and require lengthy computing time. Hamilton (1990) shows how the switching regime filter can be estimated using the EM (expected maximum likelihood) algorithm developed by Dempster, *The Data*

The price and output measures considered for this study are monthly time series. The Federal Reserve publishes indices of industrial production associated with the Bureau of Labor Statistics' Producer Price Index commodity series at the monthly level.[10] For this study we limit ourselves to considering industries first at the two-digit Standard Industrial Classification level and then at the three-digit level if there are industry definition problems at the two-digit level.

The PPI's at various levels of aggregation are the natural choice for the price series.[11] To form a relative industry price, p_t, the aggregate PPI is used to deflate an individual industry price index. If the corresponding PPI for an industry at the two-digit SIC level is too broad, we then look at industries at the three-digit level where we can get a closer match of the production and producer price series. The industries and associated price indices included in this study are listed in Table II.

The first observation for $\mathbf{y}_t$ is either January, 1960, or the earliest date following January, 1960, when both price and production series data first become available; the final observation is December, 1995. The originally unseasonalized price and production series are also individually

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Laird, and Rubin (1977). With the EM algorithm, analytic derivatives are easily calculated from smoothed inferences. Furthermore, systems with a larger number of parameters, as in the bivariate model employed here, do not require additional iterations or computing time because the analytic derivatives are calculated from the smoothed probabilities. In addition to choosing the method for maximizing the likelihood function, another problem arises when the mean of the first state is set exactly equal to the first observation and the variance of the first state is allowed to vanish. In such a case the likelihood function blows up to infinity. Hamilton (1991) offers Bayesian priors as a solution to this problem. These positive Bayesian priors imply that one is now maximizing a generalized objective function that is not subject to these singularities. The first order conditions from maximizing the log likelihood function with and without the Bayesian priors are given in Hamilton (1990) and Engel and Hamilton (1990). In practice we find that this potential singularity in the likelihood function is not a problem with our data.

[9] The smoothed probability, $p(s_{t-1} = i, s_t = j \mid \mathbf{y}_1,...,\mathbf{y}_T;\theta)$, is calculated as part of the filter for the two-state model employed by Engel and Hamilton. In a two-state model, the transition observations from state i in period t-1 to state j in period t are incorporated into the estimate of $\mu_{s_t=j}$ and $\Omega_{s_t=j}$. In practice we estimate a two-state model and use $p(s_{t-1} = i, s_t = j \mid \mathbf{y}_1,...,\mathbf{y}_T;\theta)$ to estimate the parameters from a four-state version of the EM equations in Hamilton (1990) (p.54).

[10] The results are similar if capacity utilization rates are used instead of industrial production.

[11] The PPI data were downloaded from the BLS World Wide Web site http://stats.bls.gov/.

deseasonalized using Harvey's (1993) basic structural model (pp. 142-44). In terms of the notation in the model described above, q_t is 100 times the difference in natural logs of the index of industrial production, and p_t is 100 times the difference in natural logs of the corresponding price index.

Estimates and Business Cycle Specification Testing

The model was estimated for twelve industries at the two-digit SIC level and five industries at the three-digit level.[12,13] The estimated persistence of both boom and recessionary states is high for all industries, so there are only a small number of months representing transitions from one state to another. Because of this, the standard errors associated with estimates of $\mu_{12}, \mu_{21}, \Omega_{12}, \text{and}\, \Omega_{21}$ are large. Therefore, in Table III we report parameter estimates for the persistent states and the estimated state transition probabilities for each of the seventeen industries.

It is clear from the estimates that the filter is capturing the dynamics of business cycles as opposed to structural changes in positive growth rates. For fourteen of the seventeen industries, the production mean growth rate is statistically different from zero in state 1. The mean change in production for state 2 is also negative for these fourteen industries, but not always statistically different from zero.[14]

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[12] We thank James Hamilton for kindly distributing his Gauss code with which we replicated his results. Additional code was added for the likelihood ratio tests and bivariate conditional moment tests.

[13] The following industries are not included: Tobacco (SIC 21), Textiles (SIC 22), Apparel SIC (23), and Instruments (SIC 38). The real price of tobacco was fairly constant from January, 1960, to August, 1982, after which it began a nearly deterministic climb from 102 in September, 1983, to 234 in July, 1993. Then the real price fell 24% in August, 1993, and does not change much for the rest of the sample. Clearly a more complicated model explaining these events is necessary before the switching regime model is applied. The BLS does not publish a price index solely for textiles, but one for Textiles and Apparel. It did publish a separate series for Apparel, but it ends in 1977. There is also no price index which adequately captures the general industry, Instruments (SIC 38). The five industries at the three-digit level represent three industries for which good measures of the price could not be found at the two-digit level.

[14] Furthermore, following Engel and Hamilton (1990) we use a general null hypothesis to test whether a series follows a random walk against the alternative of the two-state regime model. The Markov switching probabilities

The production growth rates for the newspaper (SIC 271) and metalworking machinery (SIC 354) industries are not statistically different from zero in state 1 or 2. Leather (SIC 31) production is trending down for the entire sample, and the mean growth rate in production in the food (SIC 20) industry is constant.

An alternative empirical approach is to estimate a model in which price and quantity changes depend on the current state ($s_t \in \{1,2\}$) but not on the previous state. Such a model has two bivariate distributions for p and q, rather than four. The point estimates and the standard errors from estimating such a two-state model differ only slightly from those presented in Table III. The statistical tests (below) that compare means and variances in different states are based on estimates from this two state model that includes the effect of the transition observations $(s_{t-1} = i, s_t = j)$ on the state j estimates (see footnote 9).

A Wald statistic for testing whether the means for one of the component series, μ_{s_t}, are different across states is given by

$$\frac{(\hat{\mu}_1 - \hat{\mu}_2)^2}{\hat{\text{var}}(\hat{\mu}_1) + \hat{\text{var}}(\hat{\mu}_2) - 2\,\hat{\text{cov}}(\hat{\mu}_1, \hat{\mu}_2)},$$

which is asymptotically distributed χ_1^2. The asymptotic variance and covariance of the parameters, denoted by $\hat{\text{var}}(\hat{\mu}_{s_t})$ and $\hat{\text{cov}}(\hat{\mu}_1, \hat{\mu}_2)$, are estimated from the inverse of the negative

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are not identified in the model when $\mu_1 = \mu_2$ and $\Omega_1 = \Omega_2$, but asymptotically valid tests of the following null hypothesis do exist- H_0: $p_{11} = 1 - p_{22}$, $\mu_1 \neq \mu_2$, and $\Omega_1 \neq \Omega_2$. As in Engel and Hamilton, we test the null hypothesis of a random walk with both a Wald and likelihood ratio statistic. The Wald statistic is given by $\frac{[\hat{p}_{11} - (1 - \hat{p}_{22})]^2}{\hat{\text{var}}(\hat{p}_{11}) + \hat{\text{var}}(\hat{p}_{22}) + 2\,\hat{\text{cov}}(\hat{p}_{11}, \hat{p}_{22})} \approx \chi_1^2$. The likelihood ratio test compares the unconstrained log likelihood to the largest log likelihood when $p_{11} = 1 - p_{22}$ and is asymptotically distributed as χ_1^2. These test statistics are not reported here. The Wald test statistics are all larger (in some cases much larger) than the likelihood ratio test statistics, but the even the latter soundly rejects the null hypothesis of a random walk in favor of the two regime model. (The smallest LR statistic is greater than 68.) In sum, the switching regime model is capturing the dynamics of the business cycle for these industries.

of the matrix of second derivatives. These statistics for the production and price series are reported in Table IV. Superscripts on the means denote the series: production (q) and price (p). The growth rates of production for the two states are significantly different for eight industries at the α=.05 level of significance and ten industries at α=.10.

Figure 4 reports the estimated smoothed probability, $p(s_t|\mathbf{y}_1,...,\mathbf{y}_T;\hat{\theta})$, that the industry is in the recessionary regime (state 2) at date t.[15] A reasonable criteria for inferring that the recessionary regime is more likely is $p(s_t=2|\mathbf{y}_1,...,\mathbf{y}_T;\hat{\theta}) > .5$. The smoothed inferences on state 2 indicate that the dates of the business cycle at the industry level are similar to the traditional NBER dates of business cycles. This first month of the recession in the mid 1970's is nearly uniform among these 17 industries, indicating that the filter is capturing the dynamics of the business cycle. For the chemical (SIC 28) industry, the filter dates the beginning of the 1973-75 recession as December, 1972, nearly a whole year earlier than the NBER date of 1973:IV. The turning point in April, 1975, however, is identical to the conventional NBER date, 1975:II. The chemical industry also experiences contractions conforming to the traditional recessions of 1980, 1981-82, and 1990-91. These, too, are present in the other industries but with more variation in the starting and ending dates. At the monthly and industry level the algorithm also indicates the common feature across industries of contractions in the early months of 1986 and in the latter half of 1994, but these rarely last more than three months.

Note that the filter typically permits a clear classification of months into regimes. The smoothed probabilities are usually very close to 0% or to 100%. There are only 6 inferences between 40% and 60% for the chemical industry. The lumber (SIC 24) industry is an exception

[15] The evolving probabilities are similar to the smoothed inferences. Using all the information in the sample reduces the "noise" in the some of probabilities within a recession. For example, six months into the 1973-75 recession, the probability of being in the recessionary state falls from 99% to 70%, but using all the information in the sample revises that estimate back to 99%.

with frequent regime switches and more months with less conclusive inferences on the state.

The estimated switching probabilities can be used to calculate the expected duration of a regime. A regime i is expected to last $(1 - p_{ii})^{-1}$ months. The postwar historical average recession according to NBER dating is 4.7 quarters which would imply that the probability of remaining in the production contraction regime is 92.01%. Many of the industries have smaller probabilities suggesting shorter recessionary periods at the industry level.

Columns 3 and 4 in Table IV report the results of Wald tests of the null hypothesis that the growth rate of real prices is identical for both regimes. The chemical (SIC 28) industry is the only industry with countercyclical pricing trends, and the nonferrous metals industry (SIC 33:3-6, 9) is the only industry with strong procyclical trends in real prices.

Estimates of the Price Variance

The primary testable implication of our non-collusive oligopoly model is that the variance of the price changes, $\sigma^2_{s_t,p}$, is greater in the recessionary regime than during times of production growth. Using a likelihood ratio test, the null hypothesis that we now test is

$$H_0:\ \sigma^2_{1p} = \sigma^2_{2p}.$$

The results from these tests are reported in Table V.

For every industry, save one, we can reject the null hypotheses of equal price change variance draws across regimes. As the estimates in Table III show, the recessionary variance for price changes is anywhere from 6 to 17 times the expansionary variance. For these sixteen industries, the average ratio of the state 2 price variance to the state 1 price variance is 11.69. Because the inferred probabilities of being in either state are usually close to 0% or to 100%, we are confident that the prices are much more variable in a recession than in an expansion.

The lone exception is the nonferrous metals industry (SIC 33:3-6, 9) for which the point estimates of the price variance are nearly identical. This classification includes the aluminum industry. Notice from Tables III and IV that the nonferrous metals industry is the only industry which has different mean price growth rates across regimes *and* which has negative price changes in recessions and positive price changes in expansions. Using $p(s_t = 2|\mathbf{y}_1,...,\mathbf{y}_T;\hat{\theta}) >$ .5 as the criteria for dating a recession, the levels of the real price by state are shown in Figure 5 for the nonferrous metals industry. Prices almost uniformly rise during expansions and fall during recessions, and as mentioned earlier, these price changes have equal variances. The sharp rise in the level of real prices as the industry reaches the peak of the business cycle is consistent with the Bresnahan and Suslow (1989) model in which firms are producing at the vertical portion of the short run supply curve. Bresnahan and Suslow document how competition has increased in the aluminum market by observing that the Herfindahl index and concentration ratios fall for the U.S. aluminum industry from 1957-1982. It appears that there is too much competition in the Aluminum Industry for firms to set a price markup above the short run competitive price when demand is low.[16]

In addition to our theory, another source of increased price variation during contractions may be more variable input prices. This explanation, however, is not consistent with current New Keynesian research on labor markets, which contends that real wages are rigid because firms pay efficiency wages (see Yellen (1984)). Furthermore, the estimates from the machinery industry (SIC 35) seem to indicate that input costs are not likely responsible for the increase in the price change variance. All three-digit machinery industries plausibly have similar mixes of the same inputs. If input cost variation is responsible for the price variation in both recessions and expansions, then a testable prediction is that the price change variance is the same in recessions and expansions for the three-digit machinery industries. As Table III indicates, the

[16] cf ft. 5. If $n+1 > \overline{a}/(\overline{a}-\underline{a})$ then Nash equilibrium prices correspond to the short run competitive price.

point estimates for the expansionary price change variance are identical (.168) for the agricultural machinery (SIC 352) and metalworking machinery (SIC 354) industries, but they differ in recessions, 1.620 and 2.341, respectively. This suggests that these two industries with similar inputs have different oligopoly pricing in recessions.

The food (SIC 20) industry may also provide some insight into how much of the increase in the price variance may be due to economy-wide reasons other than oligopoly pricing incentives. Our theory of oligopoly pricing may not be applicable to this industry because production in the food industry is growing at a constant rate throughout the sample (see Table III). Nevertheless, the filter estimates two empirically distinct regimes. Figure 4a illustrates that food industry is in regime 2 from 1973-1981 and from 1990-91. The former time period was a period of high inflation and general economic stagnation and the latter was the 1990-91 recession. As Table V reports, the two regimes for the food industry have statistically different price change variances, apparently for reasons not due to oligopoly pricing incentives. If this is a macroeconomic phenomenon, it may be a component of the state 2 price variances for the other industries which do experience expansions and contractions. However, the food industry's price change variance only increases by a factor of *six*, the smallest of all the significantly different variances (see Table V). For the fourteen industries which have distinct expansionary and recessionary states, the average ratio of the state 2 price change variance to the state 1 price change variance is 12.20. This suggests that if there is a macroeconomic source for a higher price change variance in recessions, it is not responsible for all of the increased variance. Moreover, as the next subsection discusses, for the fourteen industries with expansions and contractions we find support for the additional prediction on the change in the form of the price change distribution.

Distribution of Price Draws

We have assumed that $\mathbf{y}_t$ has bivariate normal distributions in all states. Assuming that expansionary price changes come from a normal distribution, the model predicts that recessionary price changes come from a non-normal distribution because firms use non-normal mixed strategy distributions for prices during recessions.[17] Following the work of Newey (1985) and Hamilton (1996), we make use of the score statistics in tests that certain moment restrictions of the normal distribution hold for the data for both regimes. In particular, we will take the standard approach and examine the third and fourth moments, jointly and individually for each series. The null hypothesis then implies the following expectations hold for the joint test:

$$E\left\{\sum_{s_t=1}^{2} p(s_t = S_t|\mathbf{y}_1,\ldots,\mathbf{y}_T;\theta)(\mathbf{y}_t - \boldsymbol{\mu}_{s_t})^3\right\} = 0 \text{ and}$$

$$E\left\{\sum_{s_t=1}^{2} p(s_t = S_t|\mathbf{y}_1,\ldots,\mathbf{y}_T;\theta)\cdot\left[(\mathbf{y}_t - \boldsymbol{\mu}_{s_t})^4 - 3\begin{bmatrix}\sigma^4_{s_t,q}\\ \sigma^4_{s_t,p}\end{bmatrix}\right]\right\} = 0$$

Hamilton (1996) provides the scores for the univariate case, which can be naturally extended to the bivariate model. The sample counterparts to the above moment restrictions are

$$\mathbf{r} = \frac{1}{T}\sum_{t=1}^{T}\begin{bmatrix}\sum_{s_t=1}^{2} p(s_t = S_t|\mathbf{y}_1,\ldots,\mathbf{y}_T;\hat{\theta})(\mathbf{y}_t - \hat{\boldsymbol{\mu}}_{s_t})^3 \\ \sum_{s_t=1}^{2} p(s_t = S_t|\mathbf{y}_1,\ldots,\mathbf{y}_T;\hat{\theta})\cdot\left[(\mathbf{y}_t - \hat{\boldsymbol{\mu}}_{s_t})^4 - 3\begin{bmatrix}\hat{\sigma}^4_{s_t,q}\\ \hat{\sigma}^4_{s_t,p}\end{bmatrix}\right]\end{bmatrix}.$$

Let $\mathbf{M}$ be the $T \times 4$ matrix whose t^{th} row is given by

$$\left(\sum_{s_t=1}^{2} p(s_t = S_t|\mathbf{y}_1,\ldots,\mathbf{y}_T;\theta)(\mathbf{y}_t - \boldsymbol{\mu}_{s_t})^3\right)', \left(\sum_{s_t=1}^{2} p(s_t = S_t|\mathbf{y}_1,\ldots,\mathbf{y}_T;\theta)\cdot\left[(\mathbf{y}_t - \boldsymbol{\mu}_{s_t})^4 - 3\begin{bmatrix}\sigma^4_{s_t,q}\\ \sigma^4_{s_t,p}\end{bmatrix}\right]\right)',$$

[17] Even though the recessionary price changes may not be Gaussian, the estimates in Table III are consistent quasi-maximum likelihood estimates.

and let the matrix $\mathbf{D}$ be the $T \times 12$ matrix of scores. For $\mathbf{S} = \frac{1}{T}(\mathbf{M}'\mathbf{M} - \mathbf{M}'\mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'\mathbf{M})$, the Wald statistic, $T\mathbf{r}'\mathbf{S}^{-1}\mathbf{r}$, is asymptotically distributed as a χ_4^2 and tests whether q_t and p_t are jointly normally distributed. For only testing one restriction (column) of $\mathbf{M}$, the test statistic is asymptotically χ_1^2.

The results of the joint and individual tests for skewness and kurtosis are reported in Table VI. Column 2 reports the statistic for the joint test of normality for both regimes. There are clear rejections for all industries except food (SIC 20). Most of the individual series reject the null hypotheses of no skewness and/or kurtosis equal to 3. Recall that the moments being tested include both states.

Histograms of the price draws by state are shown in Figure 6. A price change is considered to be in state j (j = 1, 2) if $p(s_t = j|\mathbf{y}_1,\ldots,\mathbf{y}_T;\hat{\theta}) > .5$. These histograms for the price draws in state 1, the expansionary state, appear to be consistent with a normal distribution whereas the state 2 draws clearly are not. The variances of these draws are larger as our tests above indicate, and the skewness and non-normal kurtosis detected in the conditional moment tests is apparently coming from the recessionary price draws. Many of the industries have state 2 price draws with means shifted to the left, but with longer tails to the right.[18] Other industries like electrical machinery (SIC 36) and metalworking machinery (SIC 353) appear to have bi-modal price distributions during recessions.

Comparing Predictions of Collusive and Non-Collusive Models

Rotemberg and Saloner (1986) analyze a repeated game model of oligopoly pricing in which demand fluctuates randomly and independently over time. Firms are informed about the

[18] These conditional moments tests are influenced, but not overwhelmingly so, by a common outlier in August, 1973. Food prices jumped 9% that month causing the overall PPI to rise abruptly. For many industries, this real

current level of demand when they set prices, but are uncertain of future demand levels. Rotemberg and Saloner show that a firm participating in a collusive group may have more incentive to defect during a boom period than during a low demand period, because the short term gains from defection are relatively large. Thus, an optimal collusive mechanism may involve lower prices (or markups over marginal cost) during booms than during recessions, in order to eliminate the incentive to defect.

A recent paper by Bagwell and Staiger (1997) presents a theory of collusive pricing with demand alternating between expansionary and recessionary phases. Their formulation allows for autocorrelation in demand shocks. They prove that the prices for an optimal collusive mechanism are weakly procyclical when growth rates are positively correlated over time. Our empirical analysis shows that growth rates are positively correlated over time for most U.S. manufacturing industries. However, a variety of approaches are consistent with procyclical pricing, including our non-collusive oligopoly model, a theory of competitive pricing with rising marginal costs, and the Cournot oligopoly theory. Another prediction in Bagwell and Staiger (1997) is that a higher transitory demand shock (within a recessionary regime or a boom regime) is associated with a lower most-collusive price. This would generate a negative covariance between price change and quantity change within recessions and within booms. Table III reports our estimates of these covariances (see the results for Ω_{11} and Ω_{22}). There are about as many positive as negative covariances; for most industries the covariance is not significantly different from zero. Thus, the evidence does not support the unique prediction of an optimal collusion regarding transitory demand shocks. In contrast, the evidence supports the unique predictions of our non-collusive oligopoly model regarding price change variances and distributions. We should point out that these conclusions are based on an examination of a number of industries at

price draw around -5% is the *lone* outlying negative real price change.

a fairly high level of aggregation (two- and three-digit SIC). The optimal collusion theory may work very well for some selected industries in which collusion is likely to be successful. However, it does not appear to be operative for a large number of U.S. manufacturing industries.

III. Concluding Remarks

Our analysis of pricing over the business cycle focused on a non-collusive oligopoly formulation. The theoretical analysis predicts that output price changes exhibit higher variance during recessions than during boom periods and that the form of the distribution of price changes differs across recession and boom periods. The analysis also predicts that the markup of output price over the short run competitive price (conditional on demand and capacity levels) is higher in recessions than in booms. Evidence from U.S. manufacturing industries is consistent with the hypothesis that price changes have higher variance in recessions than in booms. In fact, price changes are much more variable in recessions than in booms for almost all industries studied. In addition, the frequency distributions of these price changes in recessions are distinctly unlike their expansionary counterparts. These empirical results complement the direct support for the non-collusive oligopoly model from laboratory experiments reported in Wilson (1997).

Our empirical analysis does not attempt to measure directly price-cost margins or price markups over the business cycle. Instead, we take an indirect approach that evaluates a key implication of our pricing model. The evidence is consistent with the view that oligopoly firms charge prices involving a higher markup over the short run competitive price during recessions than during boom periods. This pattern of markups (as we define markups) may amplify the effects of demand shocks on output. This in turn may provide a mechanism through which oligopoly market power exacerbates the effects of aggregate demand shocks on the macroeconomy.

It should be emphasized that our formulation does not rely on any form of collusion among firms, in contrast to much of the recent Industrial Organization literature on pricing over the business cycle. At the two- and three-digit SIC level of aggregation for manufacturing industries, we find less support for a model of optimal collusion over the business cycle than for our non-collusive oligopoly model.

Future research may focus on how industry concentration is related to the variance of price changes at a more disaggregated industry level and how nature of costs affects oligopoly pricing incentives. Forming larger systems by grouping industries together may also improve estimation efficiency and increase the number of significant parameters. Since the empirical results suggest that the form of the distribution of price changes differs across recessionary and boom regimes, it would also seem worthwhile to develop a more sophisticated econometric model of the recessionary regime.

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Appendix A

Analysis of Two-Stage Game

In stage one, firm one's expected profit is,

$$\pi(x,y) = \theta r(x,y,\underline{a}) + (1-\theta)r(x,y,\bar{a}) - cx\,,$$

where $r(\cdot)$ is the expected subgame revenue, defined on p. 7. π is continuous in (x,y) since $r(\cdot)$ is continuous in these arguments. However, π is not differentiable in x for all capacity levels, so one cannot rely exclusively on first-order conditions to characterize best responses.

Consider the investment incentives for firm one, conditional on firm one being the larger firm ($x > y$). In this case assumption *A1* implies that expected profit is strictly increasing in x for $x + y < \bar{a}$; $\pi(x,y) = v(E(a) - y) - cx$ for $x + y > \bar{a}$, so that π is strictly decreasing when total capacity exceeds the high demand level; and π is continuous in x at $x = \bar{a} - y$. Therefore, if $y < \frac{1}{2}\bar{a}$ then π reaches a local maximum at $x = \bar{a} - y$. This may not be a global maximum since π may attain a higher value for some $x < y$.

The payoffs for firm one are more complex when it is the smaller firm ($x < y$). Consider first the best response to $y \in [\underline{a}, \bar{a}]$. Any best response will be less than $\underline{a}$, since *A2* implies that π is strictly decreasing in x for $x > \underline{a}$. Given $y \in [\underline{a}, \bar{a}]$, assumption *A2* implies that π is strictly in x for $0 \le x \le \bar{a} - y$. π is strictly concave in x for $\bar{a} - y \le x \le \underline{a}$. So, there is a unique best response to each $y \in [\underline{a}, \bar{a}]$, which lies in $\bar{a} - y \le x \le \underline{a}$. This best response is,

(A.1) $$b(y) = max\left\{\bar{a} - y, \frac{(\theta v - c)\underline{a}y + (1-\theta)v\bar{a}\underline{a}}{2(\theta v y + (1-\theta)v\underline{a})}\right\}.$$

Suppose that $y \in [\frac{1}{2}\bar{a}, \underline{a}]$. If $x \le \underline{a} - y$ then $\pi(x,y) = vx - cx$, which is strictly increasing in x. If $x \ge y$ then $\pi(x,y) = v(E(a) - y) - cx$, which is strictly decreasing in x. so any best response must be in $[\underline{a}-y,y]$. Firm one's expected profit function is not differentiable at $x=\bar{a}-y$; expected profit is strictly concave in x for $x\in[\underline{a}-y,y]$. This implies that there is a unique best response to $y\in[\frac{1}{2}\bar{a},\underline{a}]$ that lies in $[\underline{a}-y,y]$.

If the condition,

(A.2) $$\theta \le \frac{\bar{a}\left(\frac{v-c}{c}\right)}{3\bar{a}-2\underline{a}},$$

holds then the best response to $y\in[\frac{1}{2}\bar{a},\underline{a}]$ is,

(A.3) $$b(y)=max\{\bar{a}-y,\tfrac{1}{2}(E(a)-cy/v)\}.$$

From (A.3) it follows that $b(\frac{1}{2}\bar{a})=\frac{1}{2}\bar{a}$ and $b(y)=\bar{a}-y$ for some interval of y-values extending above $y=\frac{1}{2}\bar{a}$. Inequality (A.2) also implies that $\bar{a}-y$ is a best response to $y\in[0,\frac{1}{2}\bar{a})$; i.e., the local best response for firm one as a large firm is also a global best response to $y\in[0,\frac{1}{2}\bar{a})$. So, inequality (A.2) yields a reaction function for firm one that is as depicted by R_1 in Figure 2A. The reaction function for firm two is defined symmetrically. The set of equilibria is the set of capacity pairs that sum to $\bar{a}$ such that neither x nor y exceed some critical value. This critical value is the lowest value of y such that $b(y)$ in (A.1) or (A.3) exceeds $\bar{a}-y$.

If (A.2) does not hold then a best response to $y\in[\frac{1}{2}\bar{a},\underline{a}]$ may be less than $\bar{a}-y$. For some values of $y\in[\frac{1}{2}\bar{a},\underline{a}]$, expected profit for firm one is maximized by choosing capacity,

$$\tilde{x}(y)\equiv\tfrac{1}{2}[\underline{a}+(1-\theta-c/v)y/\theta].$$

This capacity choice is optimal for firm one when $\tilde{x}(y) < \bar{a} - y$, which is possible only when (A.2) does not hold. If (A.2) does not hold then $\tilde{x}(\frac{1}{2}\bar{a}) < \frac{1}{2}\bar{a}$ and $\tilde{x}(y) < \bar{a} - y$ for an interval of y-values exceeding $\frac{1}{2}\bar{a}$. The best response to $y \in [\frac{1}{2}\bar{a}, \underline{a}]$ is,

(A.4) $$b(y) = min\{\tilde{x}(y), max\{\bar{a} - y, \tfrac{1}{2}(E(a) - cy / v)\}\}.$$

If (A.2) does not hold there is also an interval of y-values below $\frac{1}{2}\bar{a}$ for which the best response is $\tilde{x}(y) < \bar{a} - y$. In such cases, there is a local maximum that involves firm one being the large firm and choosing capacity, $\bar{a} - y$; however, the global maximum is for firm one to respond as a small firm, choosing $\tilde{x}(y) < y$. Once y becomes sufficiently small, firm one's best response "jumps" up to $\bar{a} - y$. The reaction correspondence for firm one is depicted as R_1 in Figure 2B. The set of equilibria is the set of capacity pairs that sum to $\bar{a}$ such that, (1) neither x nor y exceed a critical value defined in the previous paragraph and, (2) an interval of capacity pairs around $x = y$ is excluded (when firm two is the large firm, the excluded set involves y-values such that $\tilde{x}(y) < \bar{a} - y$).

Appendix B

This appendix illustrates the derivations of the results presented in Table I for the predicted price and quantity changes. We define $p_t \equiv \ln P_t - \ln P_{t-1}$ and $q_t \equiv \ln Q_t - \ln Q_{t-1}$ where P_t is the average price and Q_t is production in period t. The approximations of p_t use a first order Taylor expansion:

$$ln(x+y) \approx ln(E(x)+E(y)) + \frac{x-E(x)+y-E(y)}{E(x)+E(y)}.$$

A derivation for the case, $s_{t-1} = 1$ and $s_t = 2$, is provided here. Derivations for the other three cases in Table I are similar to this. The period t price is the sum of the short run marginal cost, b_t , and a markup term, m_{1t} , where $m_{1t} \in (0,v]$, $E(m_{1t}) = \overline{m}_1 < v$, *and* $Var(m_{1t}) = \sigma^2_{m_1}$.

The price in $t-1$ is, $b_{t-1} + v$. Thus we have,

$$p_t = ln(b_t + m_{1t}) - ln(b_{t-1} + v) \approx ln\left(\frac{\overline{b} + \overline{m}_1}{\overline{b} + v}\right) + \frac{b_t + m_{1t} - \overline{b} - \overline{m}_1}{\overline{b} + \overline{m}_1} - \frac{b_{t-1} - \overline{b}}{\overline{b} + v},$$

which is linear in b_t, m_{1t}, and b_{t-1}, and

$$q_t = ln\, a_t - ln\, a_{t-1} = ln(\tau_2).$$

The first and second moments are:

$$E(p_t) = ln\left(\frac{\overline{b} + \overline{m}_1}{\overline{b} + v}\right) < 0,$$

$$Var(p_t) = E\left[\left(p_t - ln\left(\frac{\overline{b} + \overline{m}_1}{\overline{b} + v}\right)\right)^2\right] = E\left[\left(\frac{b_t + m_{1t} - \overline{b} - \overline{m}_1}{\overline{b} + \overline{m}_1} - \frac{b_{t-1} - \overline{b}}{\overline{b} + v}\right)^2\right]$$

$$= \frac{\sigma_b^2 + \sigma_{m_1}^2}{(\overline{b} + \overline{m}_1)^2} + \frac{\sigma_b^2}{(\overline{b} + v)^2} = (\phi_0 + \phi_1)\sigma_b^2 + \phi_1 \sigma_{m_1}^2,$$

$E(q_t) = ln(\tau_2)$, and $Var(q_t) = 0$.

Table II
Industries and Associated Price Indices

Industry	SIC Code	Price Index (BLS series)
Foods	20	PPI, Processed foods and feeds (wpu02)
Lumber and products	24	PPI, Lumber and wood products (wpu08)
Furniture and fixtures	25	PPI, Furniture and household durables (wpu12)
Paper and products	26	PPI, Pulp, paper, and allied products (wpu09)
Newspapers	271	CPI, Newspapers (cuur0000se5901)
Chemicals and products	28	PPI, Chemicals and allied products (wpu06)
Petroleum products	29	PPI, Petroleum products refined (wpu057)
Rubber and plastic products	30	PPI, Rubber and plastic products (wpu07)
Leather and products	31	PPI, Leather (wpu042)
Clay, glass, and stone products	32	PPI, Nonmetallic mineral products (wpu13)
Nonferrous metals	33:3-6,9	PPI, Nonferrous metals (wpu102)
Fabricated metal products	34	PPI, Fabricated structural metal products (wpu107)
Agricultural machinery and equipment	352	PPI, Agricultural machinery and equipment (wpu111)
Construction machinery and equipment	353	PPI, Construction machinery and equipment (wpu112)
Metalworking machinery and equipment	354	PPI, Metalworking machinery and equipment (wpu113)
Electrical machinery and equipment	36	PPI, Electrical machinery and equipment (wpu117)
Transportation equipment	37	PPI, Transportation equipment (wpu14)

Table III
Maximum Likelihood Estimates for $\mathbf{y}_t = [q_t, p_t]'$

Parameter	Food (SIC 20)	Lumber (SIC 24)	Furniture (SIC 25)	Paper (SIC 26)	Newspaper (SIC 271)	Chemicals (SIC28)
μ_{11}^{q}	0.219	0.260	0.370	0.326	0.042	0.494
	(0.048) *	(0.118)	(0.090)	(0.076)	(0.065)	(0.043)
μ_{11}^{p}	0.041	0.057	-0.065	0.031	0.124	-0.075
	(0.030)	(0.060)	(0.020)	(0.023)	(0.034)	(0.023)
μ_{22}^{q}	0.198	-0.083	-1.117	-0.09	-0.347	-0.439
	(0.089)	(0.445)	(0.398)	(0.260)	(0.307)	(0.261)
μ_{22}^{p}	-0.168	0.033	-0.267	0.222	-0.058	0.563
	(0.128)	(0.342)	(0.282)	(0.180)	(0.336)	(0.365)
$p11$	0.991	0.941	0.985	0.976	0.986	0.981
	(0.007)	(0.025)	(0.008)	(0.011)	(0.013)	(0.010)
$p22$	0.972	0.844	0.878	0.893	0.921	0.873
	(0.023)	(0.056)	(0.077)	(0.058)	(0.060)	(0.066)
Ω_{11}	0.578 -0.067	3.062 0.203	2.852 0.010	1.549 -0.038	0.916 -0.095	0.611 -0.030
	(0.047) (0.049)	(0.308) (0.220)	(0.227) (0.071)	(0.136) (0.060)	(0.083) (0.074)	(0.052) (0.036)
	-0.067 0.241	0.203 0.775	0.010 0.141	-0.038 0.148	-0.095 0.262	-0.030 0.169
	(0.049) (0.025)	(0.220) (0.085)	(0.071) (0.012)	(0.060) (0.014)	(0.074) (0.024)	(0.036) (0.014)
Ω_{22}	0.645 -0.072	9.449 3.889	4.397 -0.017	3.502 -0.318	1.884 -0.446	2.124 -0.450
	(0.113) (0.191)	(1.201) (1.595)	(1.292) (1.244)	(0.592) (0.997)	(0.478) (0.876)	(0.633) (1.216)
	-0.072 1.418	3.889 6.888	-0.017 2.149	-0.318 1.51	-0.446 2.727	-0.450 2.431
	(0.191) (0.207)	(1.595) (1.071)	(1.244) (0.446)	(0.997) (0.193)	(0.876) (0.830)	(1.216) (0.381)

*Standard errors are in parentheses.

Table III continued

Parameter	Petroleum Refining (SIC 29)		Rubber (SIC 30)		Leather (SIC 31)		Stone, Clay, and Glass (SIC 32)		Nonferrous Metals (SIC33:3-6, 9)		Fabricated Metals (SIC 34)	
μ_{11}^{q}	0.276		0.628		-0.239		0.259		0.476		0.312	
	(0.067) *		(0.095)		(0.099)		(0.102)		(0.137)		(0.068)	
μ_{11}^{p}	-0.046		-0.092		-0.003		0.029		0.627		0.020	
	(0.083)		(0.024)		(0.091)		(0.021)		(0.140)		(0.020)	
μ_{22}^{q}	-0.018		-0.044		-0.273		-0.673		-0.713		-0.727	
	(0.131)		(0.655)		(0.200)		(0.360)		(0.378)		(0.221)	
μ_{22}^{p}	0.218		0.154		0.238		-0.044		-1.272		0.073	
	(0.442)		(0.168)		(0.371)		(0.290)		(0.214)		(0.222)	
$p11$	0.960		0.969		0.980		0.983		0.943		0.984	
	(0.016)		(0.012)		(0.038)		(0.009)		(0.032)		(0.007)	
$p22$	0.941		0.874		0.948		0.876		0.879		0.896	
	(0.022)		(0.054)		(0.047)		(0.066)		(0.059)		(0.066)	
Ω_{11}	1.043	0.131	2.714	-0.064	1.812	-0.031	3.159	0.040	2.941	-0.086	1.408	0.000
	(0.091)	(0.188)	(0.247)	(0.083)	(0.172)	(0.243)	(0.185)	(0.079)	(0.368)	(0.477)	(0.106)	(0.051)
	0.131	1.581	-0.064	0.167	-0.031	1.446	0.040	0.144	-0.086	2.069	0.000	0.134
	(0.188)	(0.146)	(0.083)	(0.015)	(0.243)	(0.180)	(0.079)	(0.012)	(0.477)	(0.191)	(0.051)	(0.011)
Ω_{22}	2.192	-0.217	18.474	0.112	4.039	0.429	4.222	-0.433	8.816	-0.092	2.244	-0.212
	(0.244)	(1.489)	(2.388)	(2.444)	(0.531)	(2.042)	(1.000)	(1.776)	(1.887)	(1.252)	(0.465)	(0.970)
	-0.217	24.796	0.112	1.587	0.429	15.310	-0.433	2.063	-0.092	1.915	-0.212	2.469
	(1.489)	(2.375)	(2.444)	(0.170)	(2.042)	(1.542)	(1.776)	(0.428)	(1.252)	(0.254)	(0.970)	(0.380)

*Standard errors are in parentheses.

Table III continued

Parameter	Agricultural Machinery (SIC 352)		Construction Machinery (SIC 353)		Metalworking Machinery (SIC 354)		Electrical Machinery (SIC 36)		Transportation Equipment (SIC 37)	
μ_{11}^{q}	0.490		0.400		0.125		0.604		0.329	
	(0.192) *		(0.092)		(0.133)		(0.080)		(0.173)	
μ_{11}^{p}	0.036		0.051		0.053		-0.071		0.036	
	(0.034)		(0.029)		(0.036)		(0.021)		(0.028)	
μ_{22}^{q}	-1.088		-1.369		-0.641		-0.297		-0.393	
	(0.543)		(0.364)		(0.347)		(0.336)		(0.980)	
μ_{22}^{p}	0.084		0.156		0.121		-0.122		-0.176	
	(0.199)		(0.293)		(0.277)		(0.307)		(0.213)	
$p11$	0.962		0.976		0.988		0.987		0.965	
	(0.019)		(0.014)		(0.050)		(0.007)		(0.018)	
$p22$	0.893		0.897		0.913		0.89		0.87	
	(0.063)		(0.060)		(0.042)		(0.080)		(0.070)	
Ω_{11}	5.629	0.066	1.964	-0.024	3.737	-0.062	1.892	-0.027	5.291	-0.033
	(0.640)	(0.167)	(0.170)	(0.086)	(0.373)	(0.131)	(0.153)	(0.059)	(0.528)	(0.130)
	0.066	0.168	-0.024	0.204	-0.062	0.168	-0.027	0.146	-0.033	0.16
	(0.167)	(0.023)	(0.086)	(0.018)	(0.131)	(0.021)	(0.059)	(0.012)	(0.130)	(0.016)
Ω_{22}	14.529	-0.439	5.957	-0.746	4.723	-1.290	3.507	-0.416	23.141	0.026
	(3.347)	(1.802)	(0.969)	(1.796)	(1.099)	(0.968)	(0.915)	(1.173)	(3.587)	(3.024)
	-0.439	1.620	-0.746	2.481	-1.290	2.341	-0.416	2.321	0.026	1.736
	(1.802)	(0.216)	(1.796)	(0.330)	(0.968)	(0.479)	(1.173)	(0.459)	(3.024)	(0.388)

*Standard errors are in parentheses.

Table IV
Tests of Different Means across Regimes

Industry	$H_0: \mu_1^q = \mu_2^q$ $H_a: \mu_1^q \neq \mu_2^q$		$H_0: \mu_1^p = \mu_2^p$ $H_a: \mu_1^p \neq \mu_2^p$	
	Wald Test	p-value	Wald Test	p-value
Food (SIC 20)	0.046	(0.830)	2.832	**(0.092)**
Lumber (SIC 24)	0.930	(0.335)	0.002	(0.969)
Furniture (SIC 25)	14.039	**(0.000)**	1.165	(0.280)
Paper (SIC 26)	2.006	(0.157)	0.951	(0.329)
Newspaper (SIC 271)	2.822	**(0.093)**	0.530	(0.467)
Chemicals (SIC 28)	19.296	**(0.000)**	7.836	**(0.005)**
Petroleum Refining (SIC 29)	3.674	**(0.055)**	0.408	(0.523)
Rubber (SIC 30)	2.638	(0.104)	0.445	(0.504)
Leather (SIC 31)	0.007	(0.933)	0.796	(0.372)
Stone, Clay, and Glass (SIC 32)	7.619	**(0.006)**	0.261	(0.610)
Nonferrous Metals (SIC 33:3-6, 9)	11.179	**(0.001)**	77.682	**(0.000)**
Fabricated Metals (SIC 34)	15.873	**(0.000)**	0.008	(0.930)
Agricultural Machinery (SIC 352)	8.881	**(0.003)**	0.047	(0.828)
Construction Machinery (SIC 353)	23.928	**(0.000)**	0.195	(0.659)
Metalworking Machinery (SIC 354)	2.495	(0.114)	0.016	(0.899)
Electrical Machinery (SIC 36)	7.764	**(0.005)**	0.085	(0.771)
Transportation Equipment (SIC 37)	1.982	(0.159)	1.197	(0.274)

Note: Statistics are asymptotically χ_1^2. Asymptotic p-values less than .1 are in bold.

Table V
Test of Different Price Variances Across Regimes

Industry	$H_0: \sigma^2_{1,p} = \sigma^2_{2,p}$ $H_a: \sigma^2_{1,p} \neq \sigma^2_{2,p}$ Likelihood Ratio Test	p-value	$\frac{\hat{\sigma}^2_{2,p}}{\hat{\sigma}^2_{1,p}}$ *
Food (SIC 20)	68.274	**(0.000)**	5.86
Lumber (SIC 24)	109.508	**(0.000)**	8.14
Furniture (SIC 25)	142.410	**(0.000)**	14.38
Paper (SIC 26)	144.794	**(0.000)**	9.84
Newspaper (SIC 271)	99.566	**(0.000)**	9.91
Chemicals (SIC 28)	421.102	**(0.000)**	13.32
Petroleum Refining (SIC 29)	256.162	**(0.000)**	15.15
Rubber (SIC 30)	149.436	**(0.000)**	8.88
Leather (SIC 31)	219.260	**(0.000)**	10.36
Stone, Clay, and Glass (SIC 32)	169.534	**(0.000)**	13.68
Nonferrous Metals (SIC 33:3-6, 9)	0.002	(0.964)	1.01
Fabricated Metals (SIC 34)	292.092	**(0.000)**	17.65
Agricultural Machinery (SIC 352)	103.262	**(0.000)**	9.23
Construction Machinery (SIC 353)	121.596	**(0.000)**	11.61
Metalworking Machinery (SIC 354)	119.200	**(0.000)**	13.54
Electrical Machinery (SIC 36)	201.972	**(0.000)**	15.20
Transportation Equipment (SIC 37)	144.254	**(0.000)**	10.29

Note: Statistics are asymptotically χ^2_1. Asymptotic p-values less than .1 are in bold.
* Both the restricted and the unrestricted likelihood functions were estimated without the Bayesian correction.

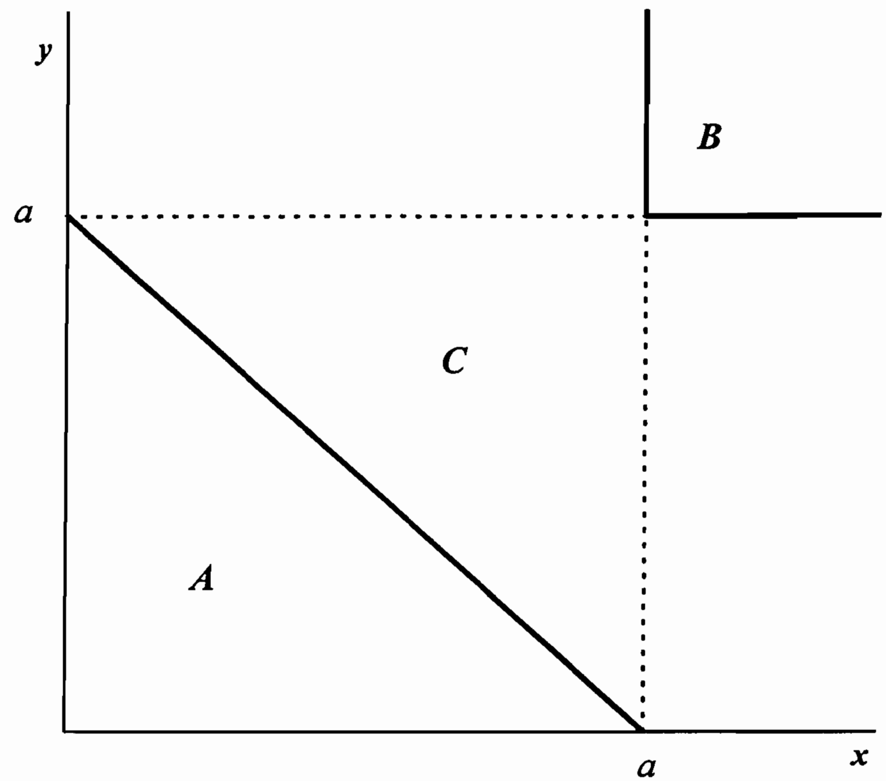
Table VI
Conditional Moment Normality Tests (Skewness and Kurtosis)*

Industry	Test: Joint Test of Normality Variable: y_t	Skewness q_t	Skewness p_t	Kurtosis q_t	Kurtosis p_t
Food (SIC 20)	2.459	0.271	1.228	0.113	0.123
	(0.652)	(0.603)	(0.268)	(0.736)	(0.726)
Lumber (SIC 24)	56.538	1.844	23.516	4.696	4.023
	(0.000)	(0.175)	**(0.000)**	**(0.030)**	**(0.045)**
Furniture (SIC 25)	18.922	0.312	7.439	2.550	1.962
	(0.001)	(0.577)	**(0.006)**	(0.110)	(0.161)
Paper (SIC 26)	8.984	3.222	4.427	4.085	3.397
	(0.062)	**(0.073)**	**(0.035)**	**(0.043)**	**(0.065)**
Newspaper (SIC 271)	15.823	2.181	10.625	3.697	2.993
	(0.003)	(0.140)	**(0.001)**	**(0.055)**	**(0.084)**
Chemicals (SIC 28)	10.670	4.349	2.088	0.309	4.218
	(0.031)	**(0.037)**	(0.149)	(0.578)	**(0.040)**
Petroleum Refining (SIC 29)	10.007	0.003	1.656	2.084	8.345
	(0.040)	(0.959)	(0.198)	(0.149)	**(0.004)**
Rubber (SIC 30)	23.788	12.757	3.774	12.229	5.255
	(0.000)	**(0.000)**	**(0.052)**	**(0.001)**	**(0.022)**
Leather (SIC 31)	9.241	3.682	0.768	2.003	4.556
	(0.055)	**(0.055)**	(0.381)	(0.157)	**(0.033)**
Stone, Clay, and Glass (SIC 32)	54.066	2.474	18.137	7.921	5.938
	(0.000)	(0.116)	**(0.000)**	**(0.005)**	**(0.015)**
Nonferrous Metals (SIC 33:3-6, 9)	24.333	0.279	0.242	0.168	23.606
	(0.000)	(0.598)	(0.623)	(0.682)	**(0.000)**
Fabricated Metals (SIC 34)	10.023	0.107	0.107	6.800	3.993
	(0.040)	(0.744)	(0.744)	**(0.009)**	**(0.046)**
Agricultural Machinery (SIC 352)	22.579	1.473	10.208	0.478	4.401
	(0.000)	(0.225)	**(0.001)**	(0.489)	**(0.036)**
Construction Machinery (SIC 353)	22.526	5.128	0.042	3.501	14.826
	(0.000)	**(0.024)**	(0.838)	**(0.061)**	**(0.000)**
Metalworking Machinery (SIC 354)	22.620	1.076	9.348	0.055	2.626
	(0.000)	(0.300)	**(0.002)**	(0.814)	(0.105)
Electrical Machinery (SIC 36)	44.848	3.755	15.090	1.693	3.317
	(0.000)	**(0.053)**	**(0.000)**	(0.193)	**(0.069)**
Transportation Equipment (SIC 37)	36.802	1.288	11.152	9.713	3.963
	(0.000)	(0.256)	**(0.001)**	**(0.002)**	**(0.047)**

Note: Column 2 statistics are asymptotically χ^2_4. Statistics in columns 3-6 are asymptotically χ^2_1. Asymptotic *p*-values less than .1 are in bold.

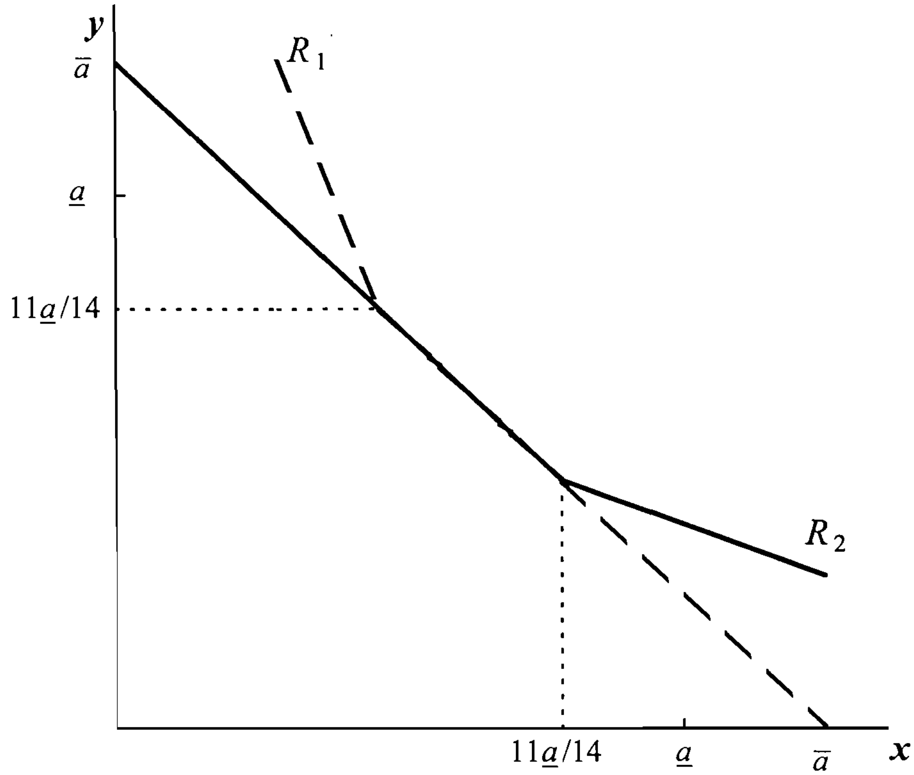
* The maximum likelihood estimates used in the calculations of the score were estimated without the Bayesian correction.

Figure 1
Capacity Regions for the Pricing Subgame



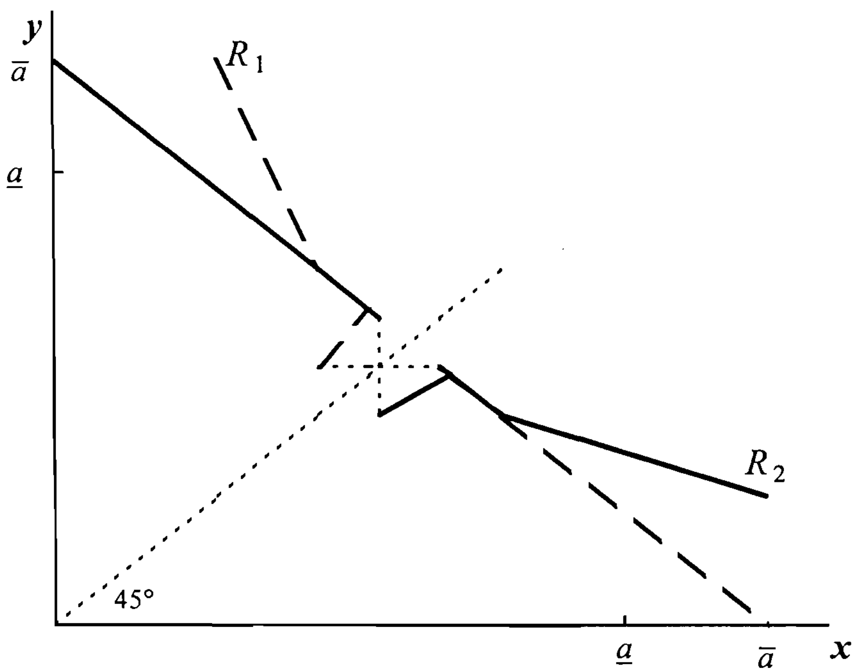
$A = \{ (x, y): x \geq 0, y \geq 0, x + y \leq a \}$
$B = \{ (x, y): x \geq a, y \geq a \}$
$C = \{ (x, y): x \geq 0, y \geq 0, (x, y) \notin A, \ (x, y) \notin B \}$

Figure 2A
Equilibrium Capacity Choices



Parameter Values: $\theta = 1/2, c/v = 1/4, \underline{a} = 5/4\bar{a}$

Figure 2B



Parameter Values: $\theta = 3/4, c/v = 1/8, \underline{a} = 5/4\bar{a}$

Figure 3
Equilibrium Mixing Distributions
$\theta = 1/2, \quad c/v = 1/3, \quad \bar{a}/\underline{a} = 5/4$

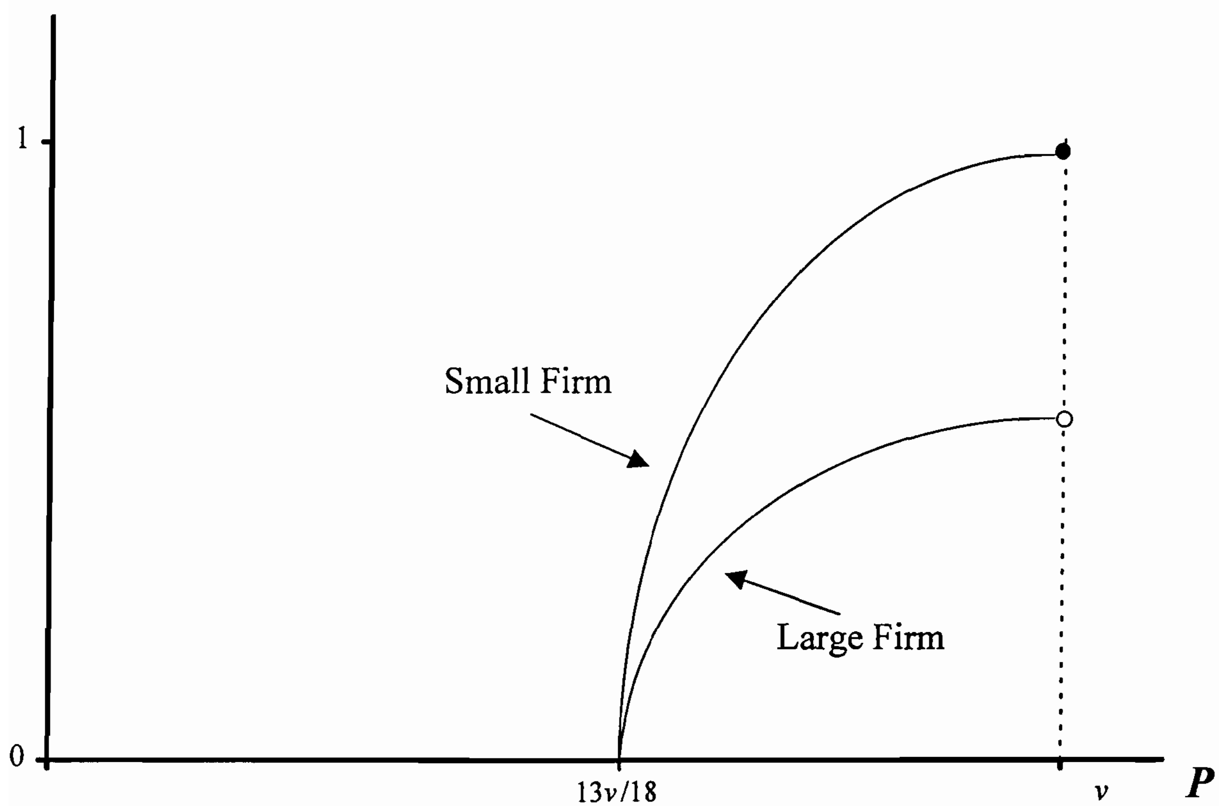
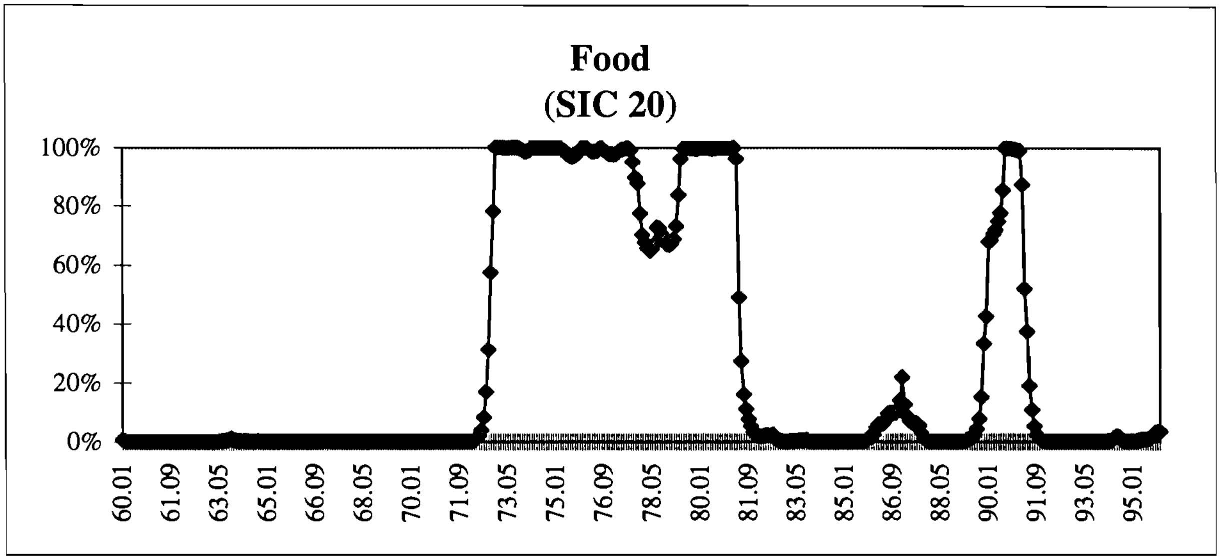
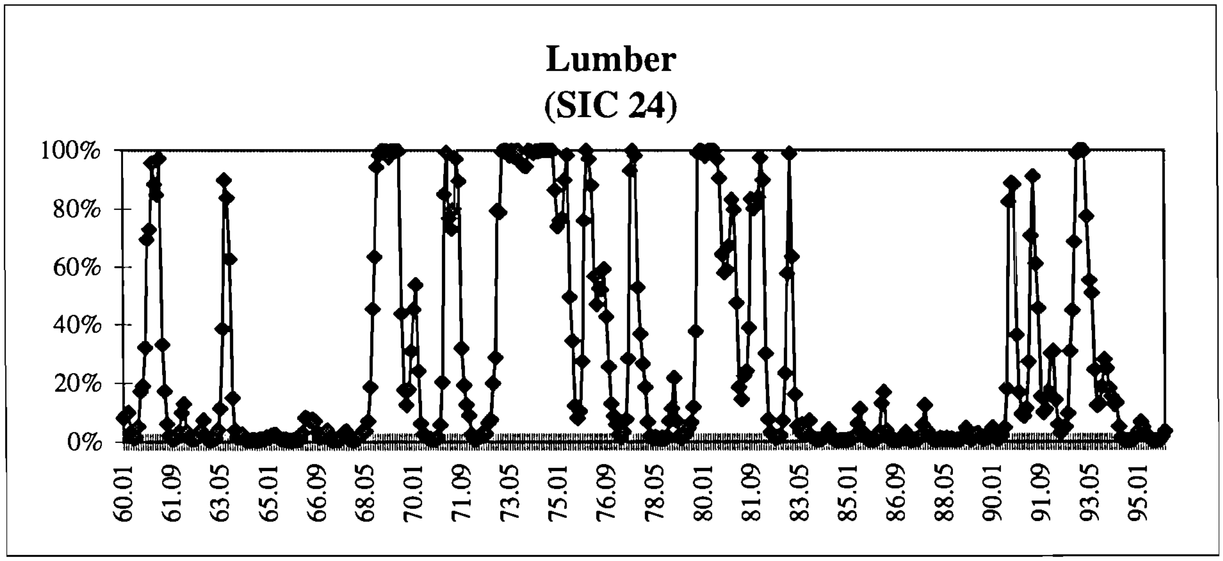


Figure 4a

Inferred Probability of Being in State 2 (Recessionary State)





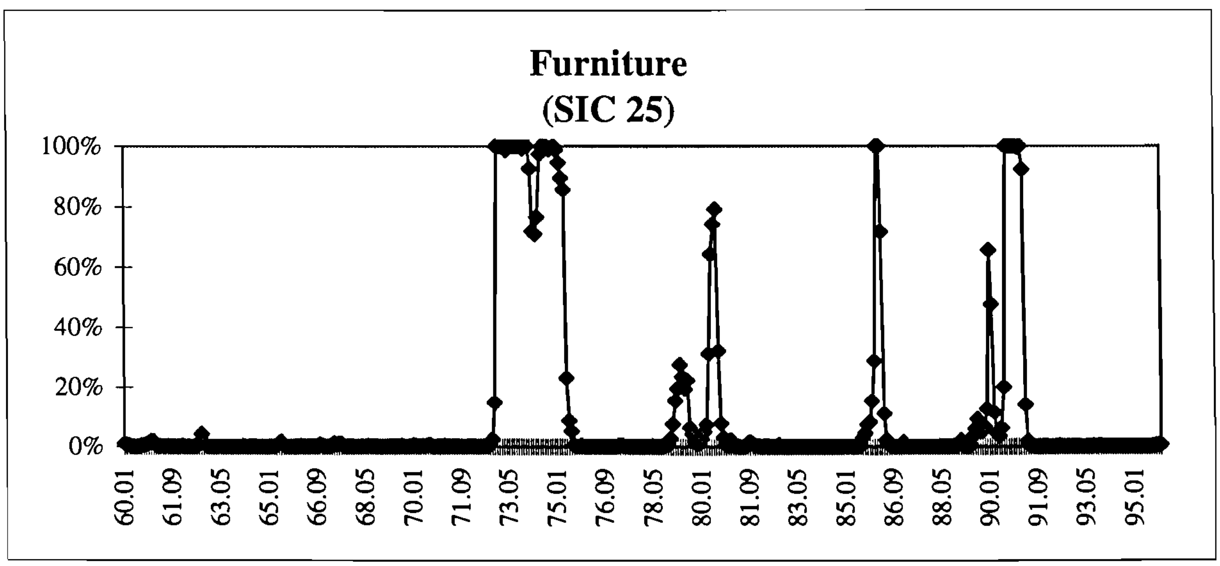
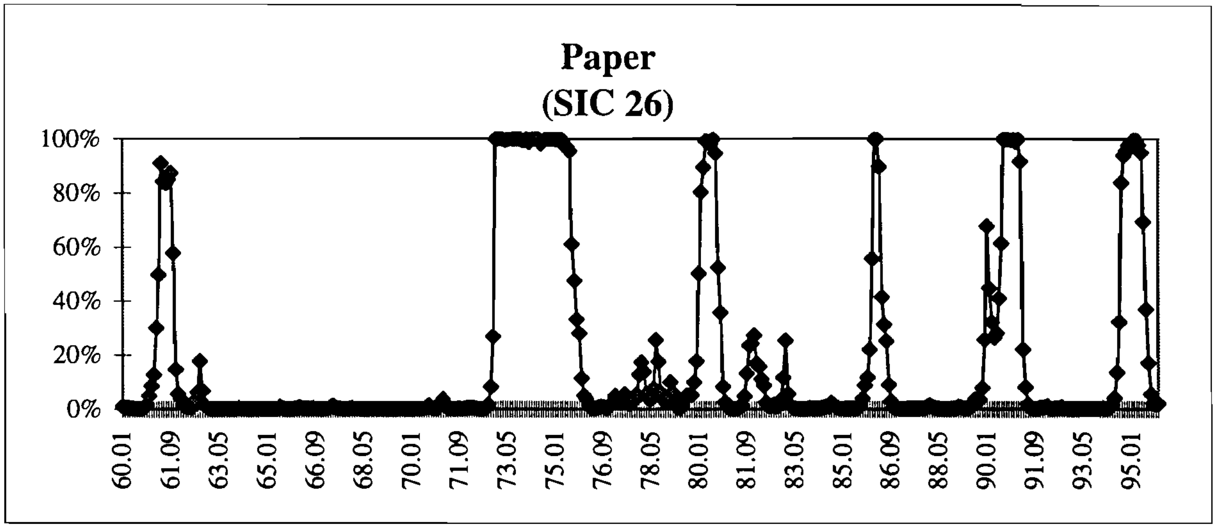
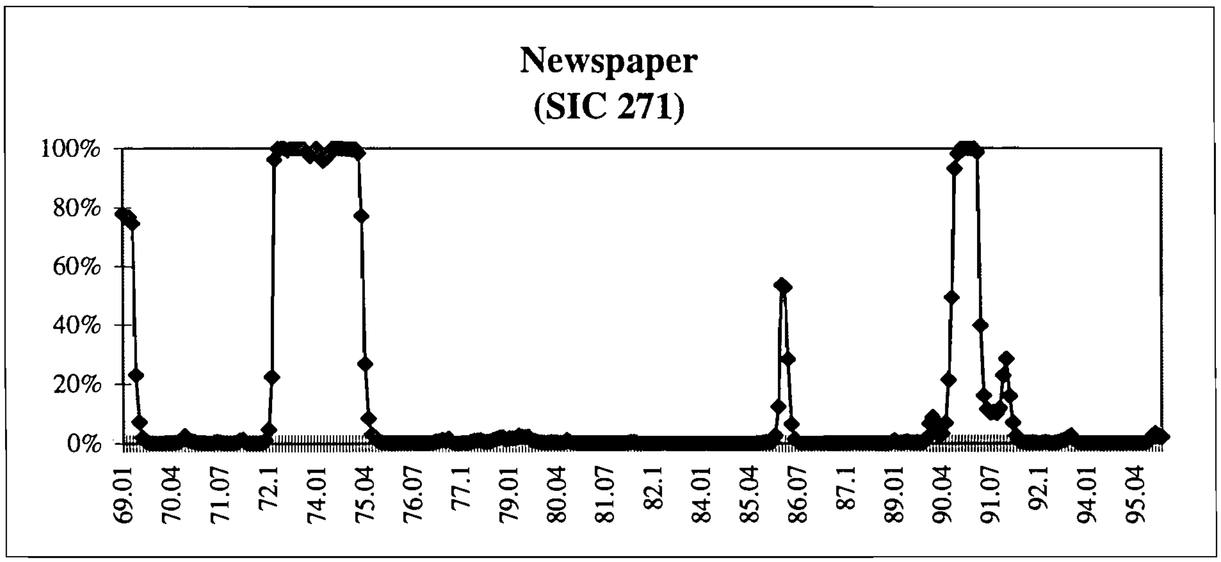


Figure 4b
Inferred Probability of Being in State 2 (Recessionary State)





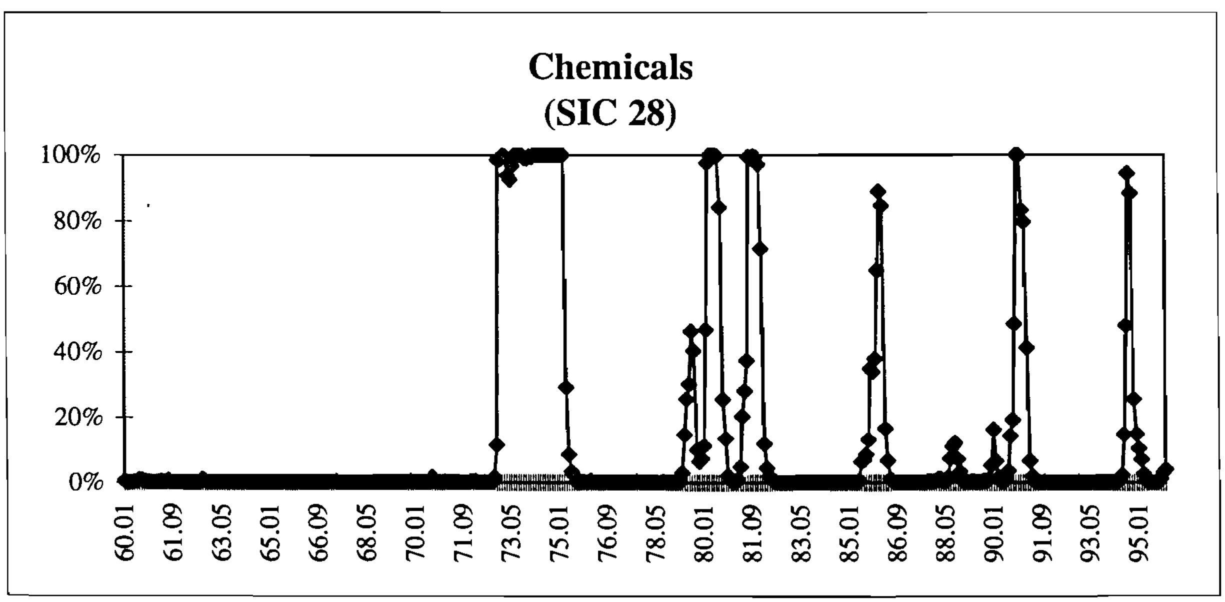


Figure 4c

Inferred Probability of Being in State 2 (Recessionary State)

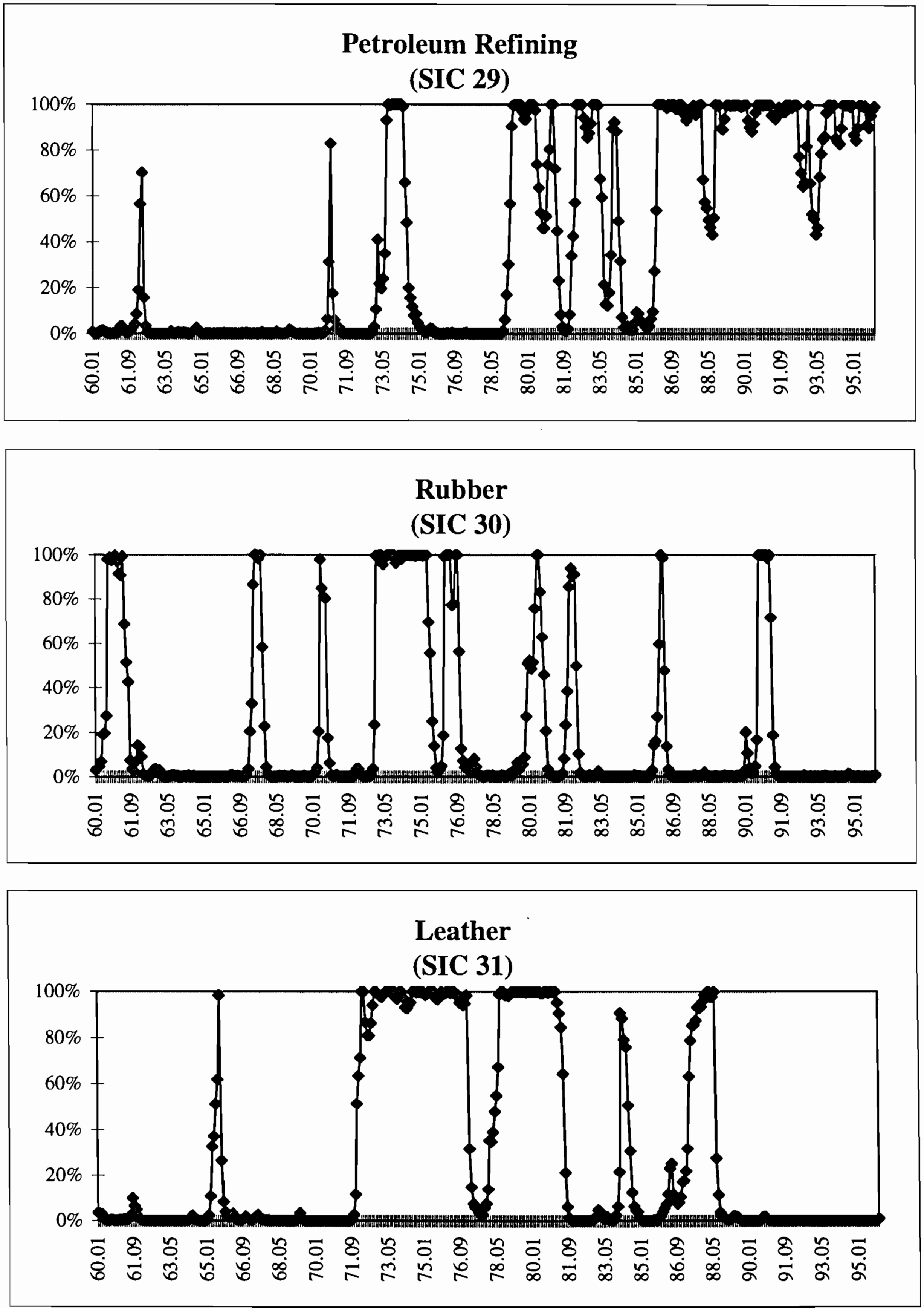
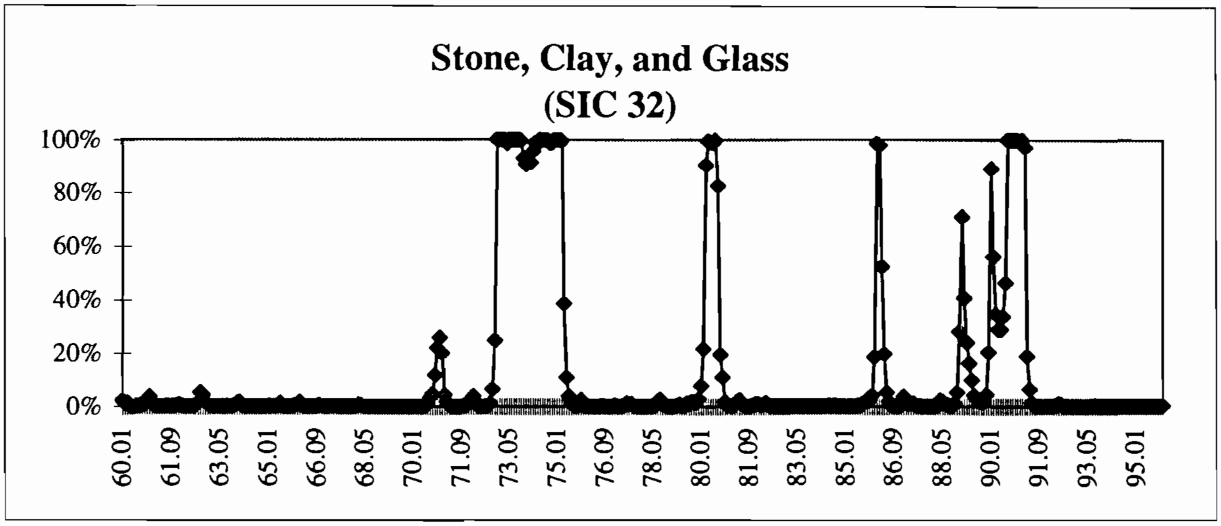
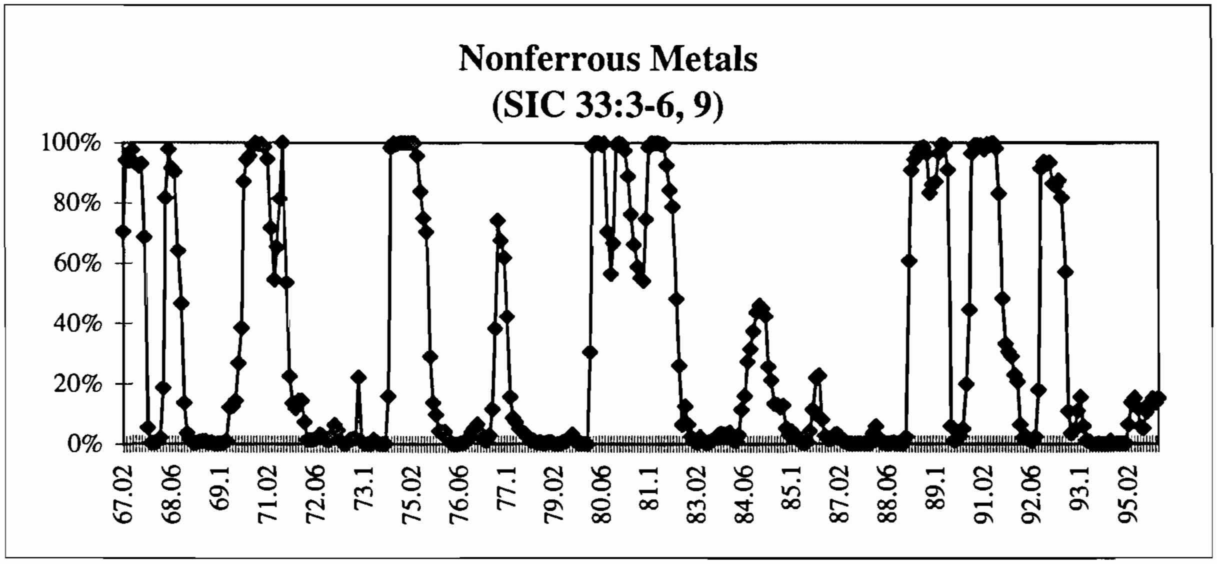


Figure 4d

Inferred Probability of Being in State 2 (Recessionary State)





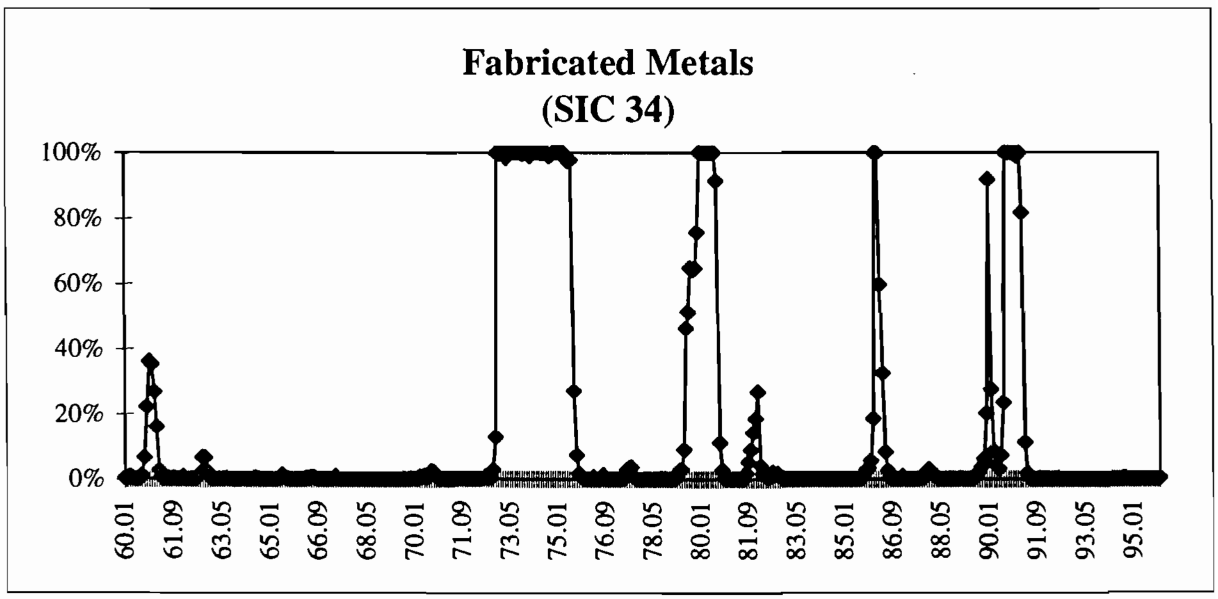
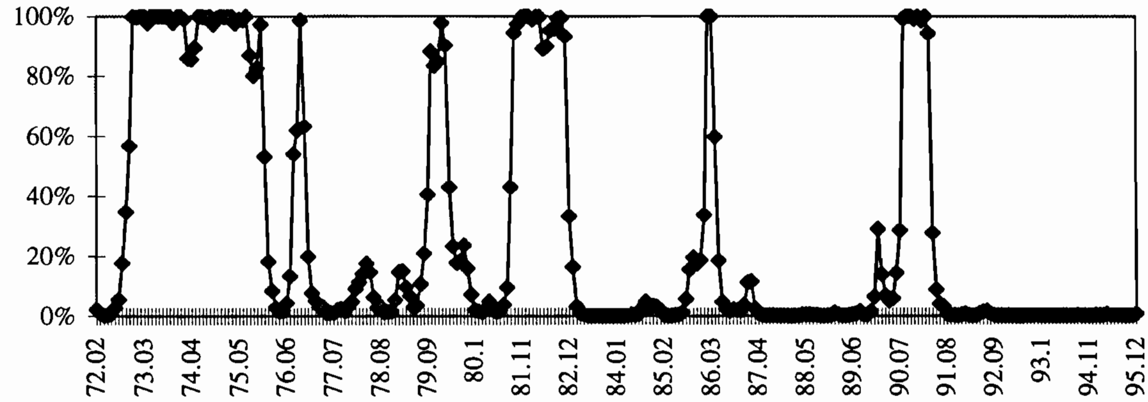


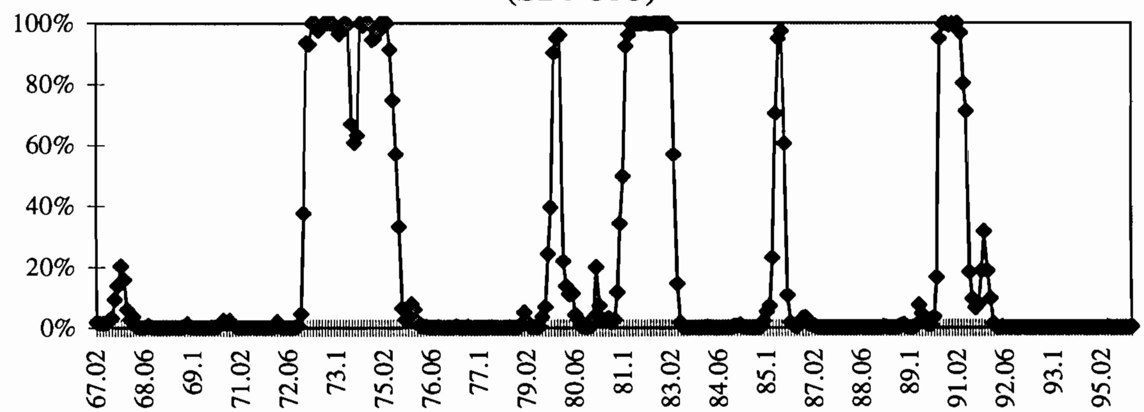
Figure 4e

Inferred Probability of Being in State 2 (Recessionary State)

Agricultural Machinery and Equipment (SIC 352)



Construction Machinery and Equipment (SIC 353)



Metalworking Machinery and Equipment (SIC 354)

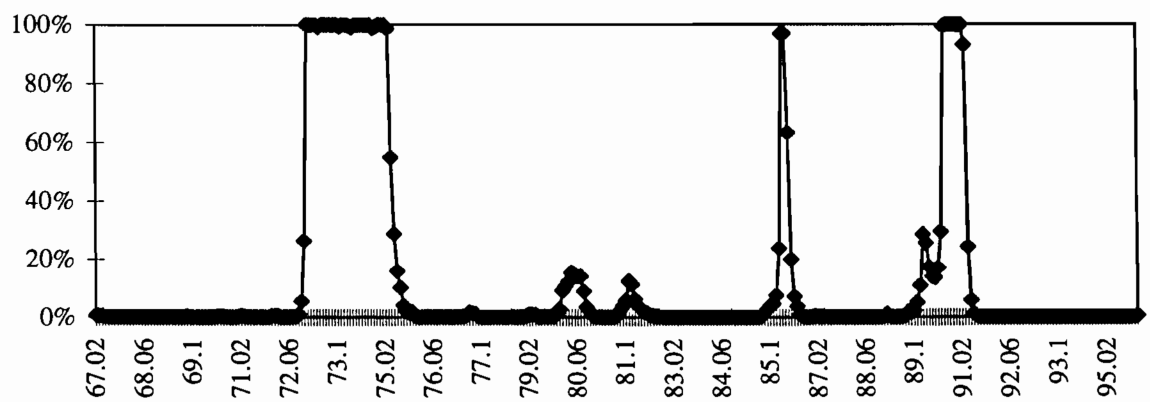
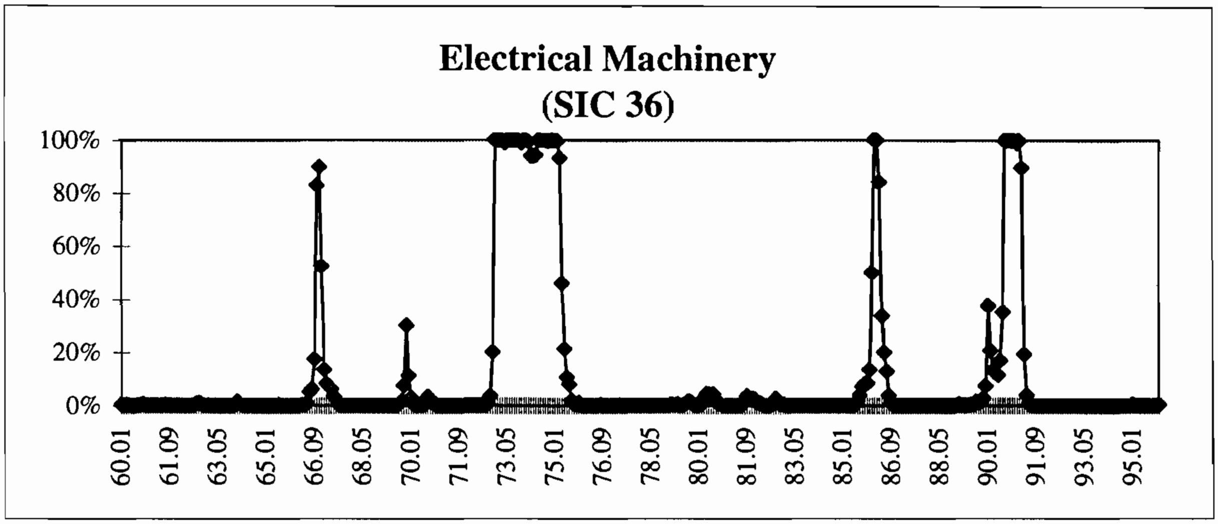


Figure 4f

Inferred Probability of Being in State 2 (Recessionary State)



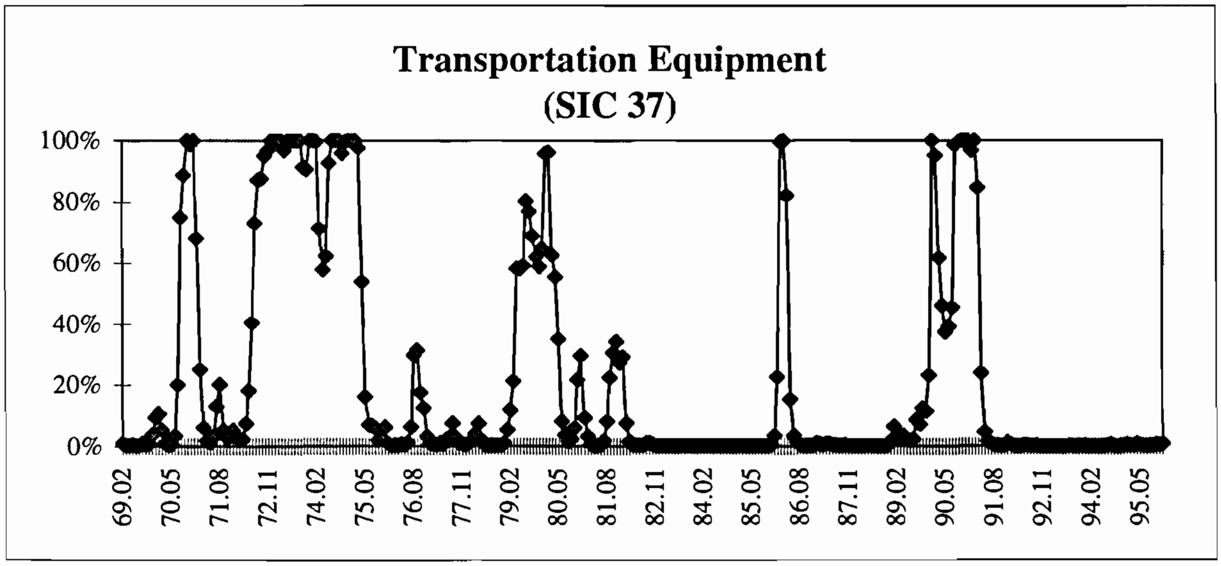


Figure 5

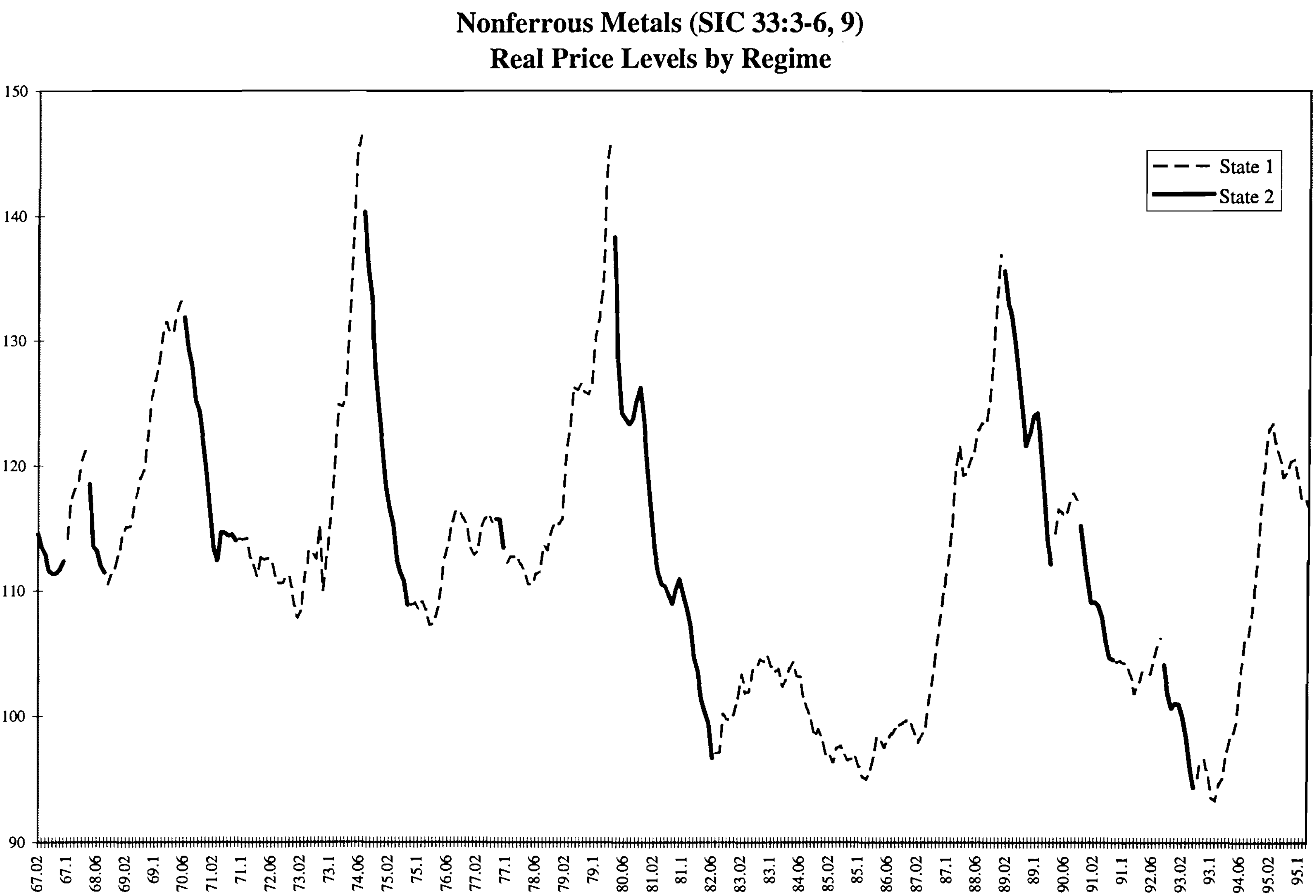

Nonferrous Metals (SIC 33:3-6, 9)
Real Price Levels by Regime
150
140
130
120
110
100
90
67.02
67.1
68.06
69.02
69.1
70.06
71.02
71.1
72.06
73.02
73.1
74.06
75.02
75.1
76.06
77.02
77.1
78.06
79.02
79.1
80.06
81.02
81.1
82.06
83.02
83.1
84.06
85.02
85.1
86.06
87.02
87.1
88.06
89.02
89.1
90.06
91.02
91.1
92.06
93.02
93.1
94.06
95.02
95.1
State 1
State 2

Figure 6a
Histogram of Price Changes by State

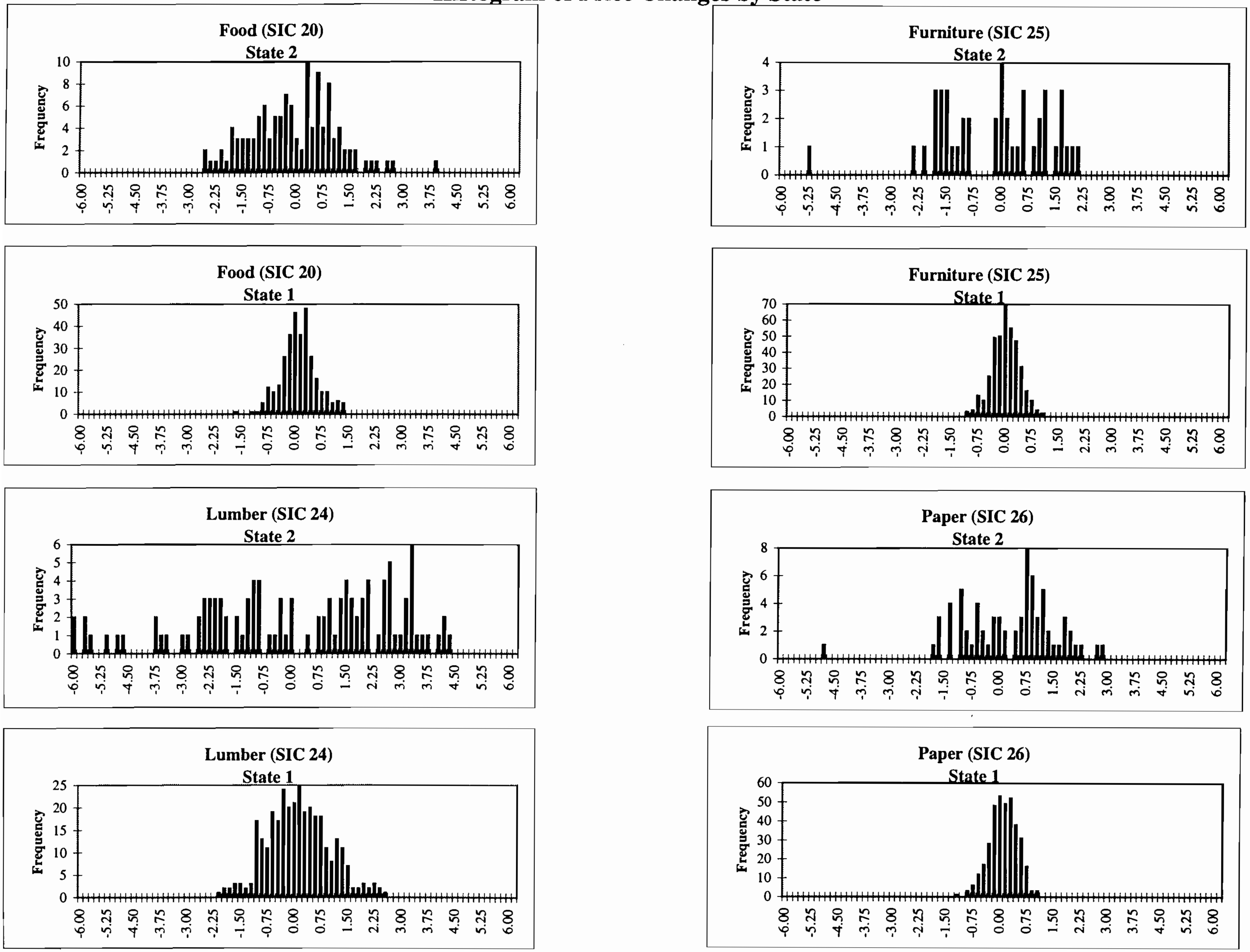
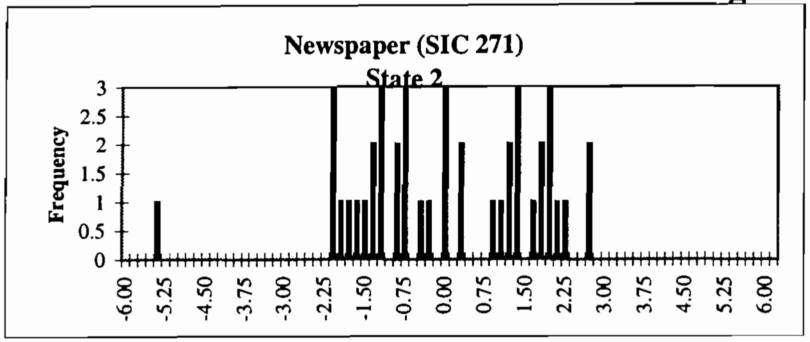
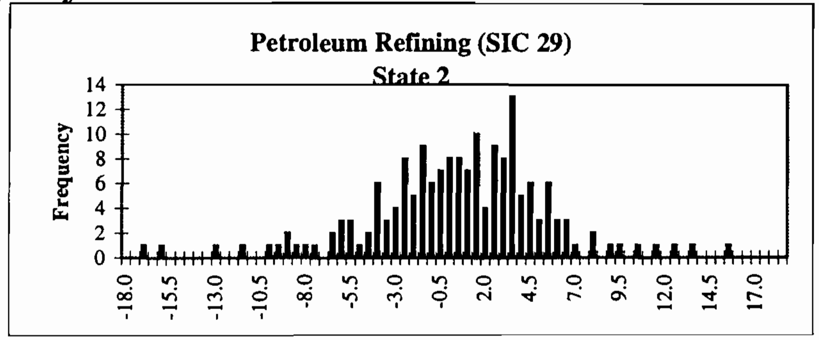
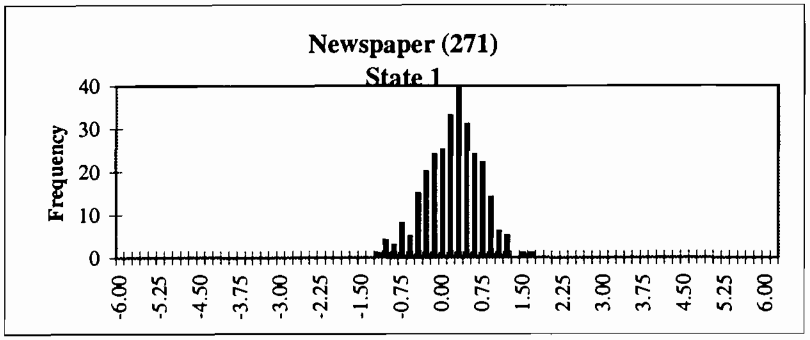
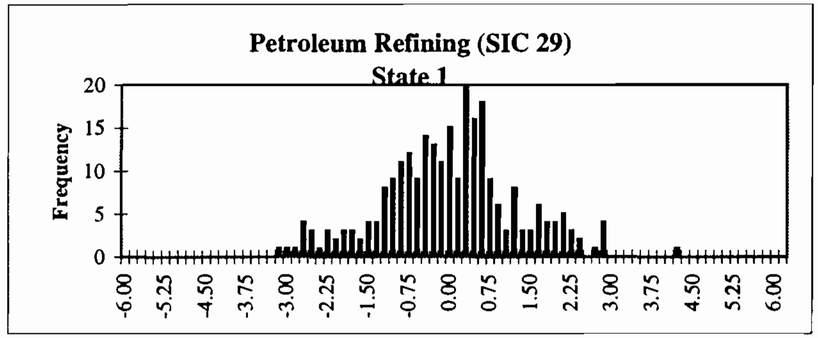


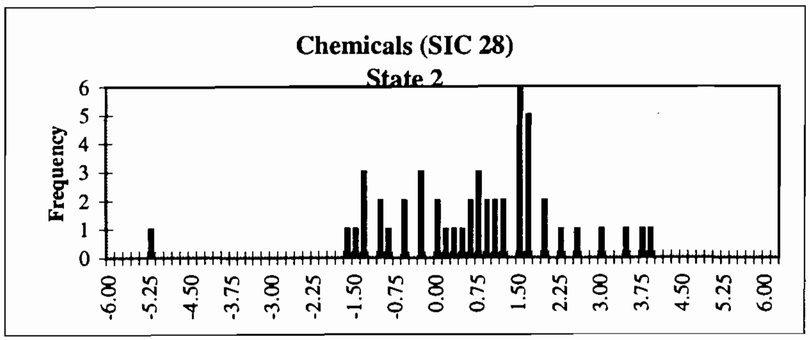
Figure 6b
Histogram of Price Changes by State

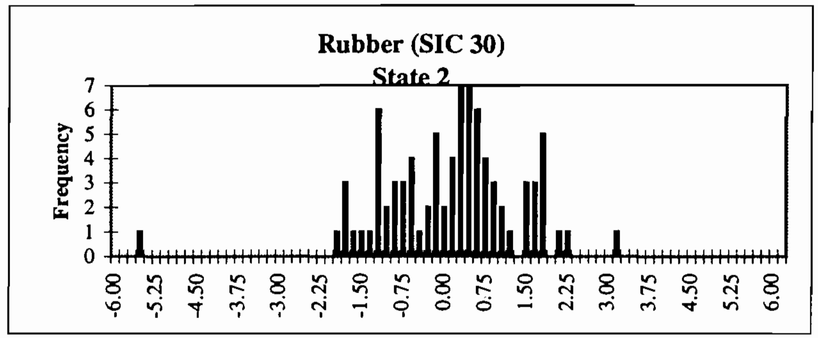


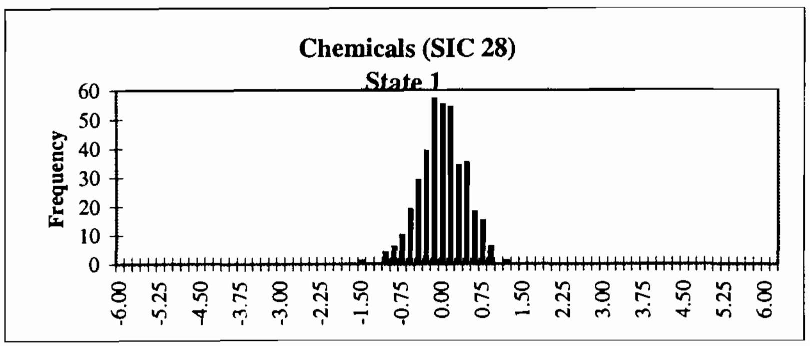












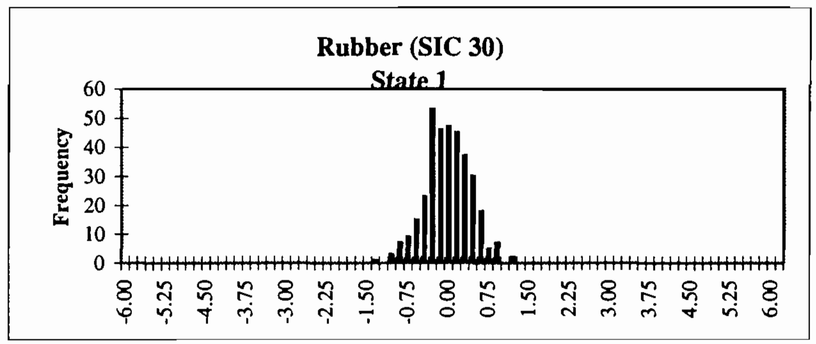


Figure 6c
Histogram of Price Changes by State

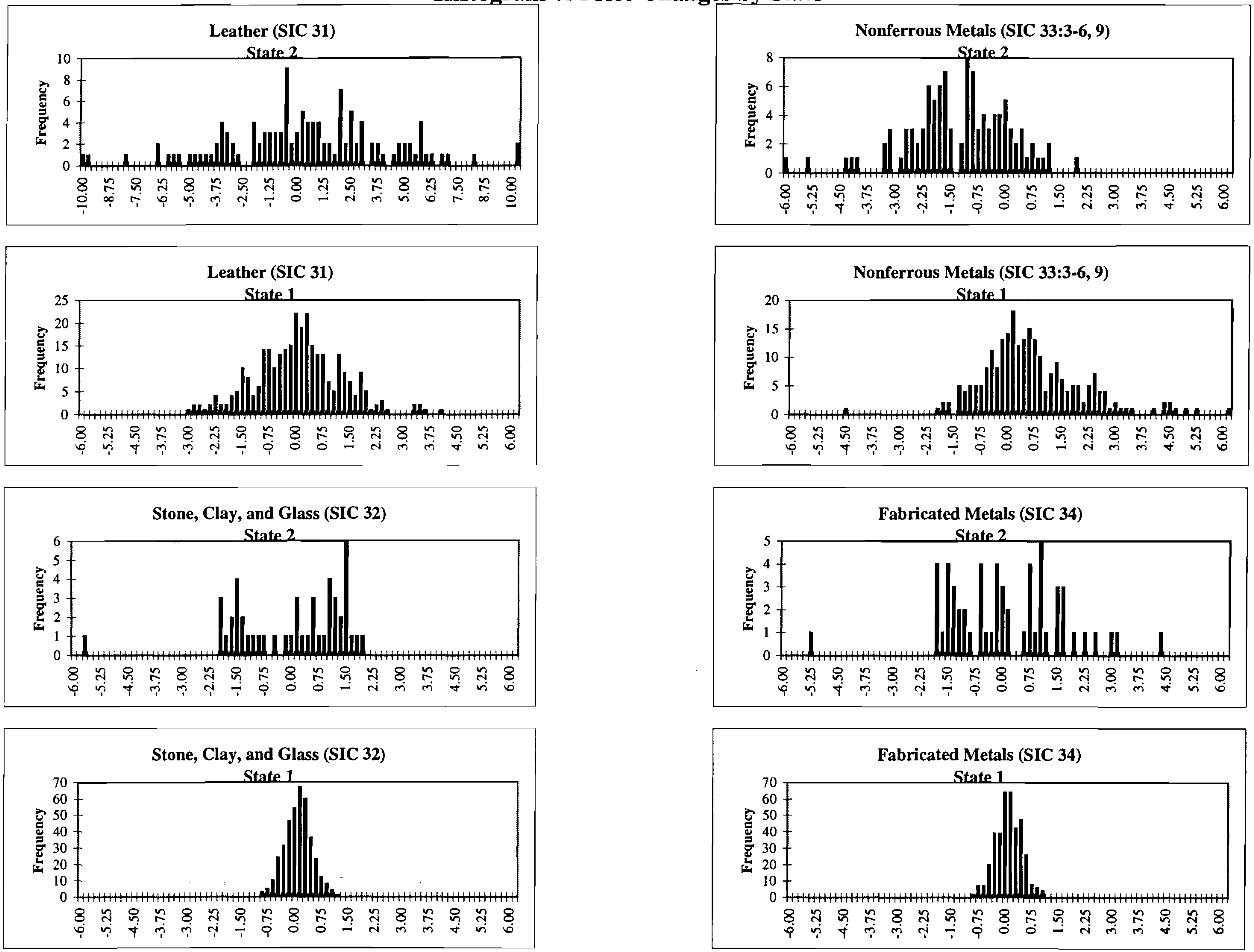


Figure 6d
Histogram of Price Changes by State

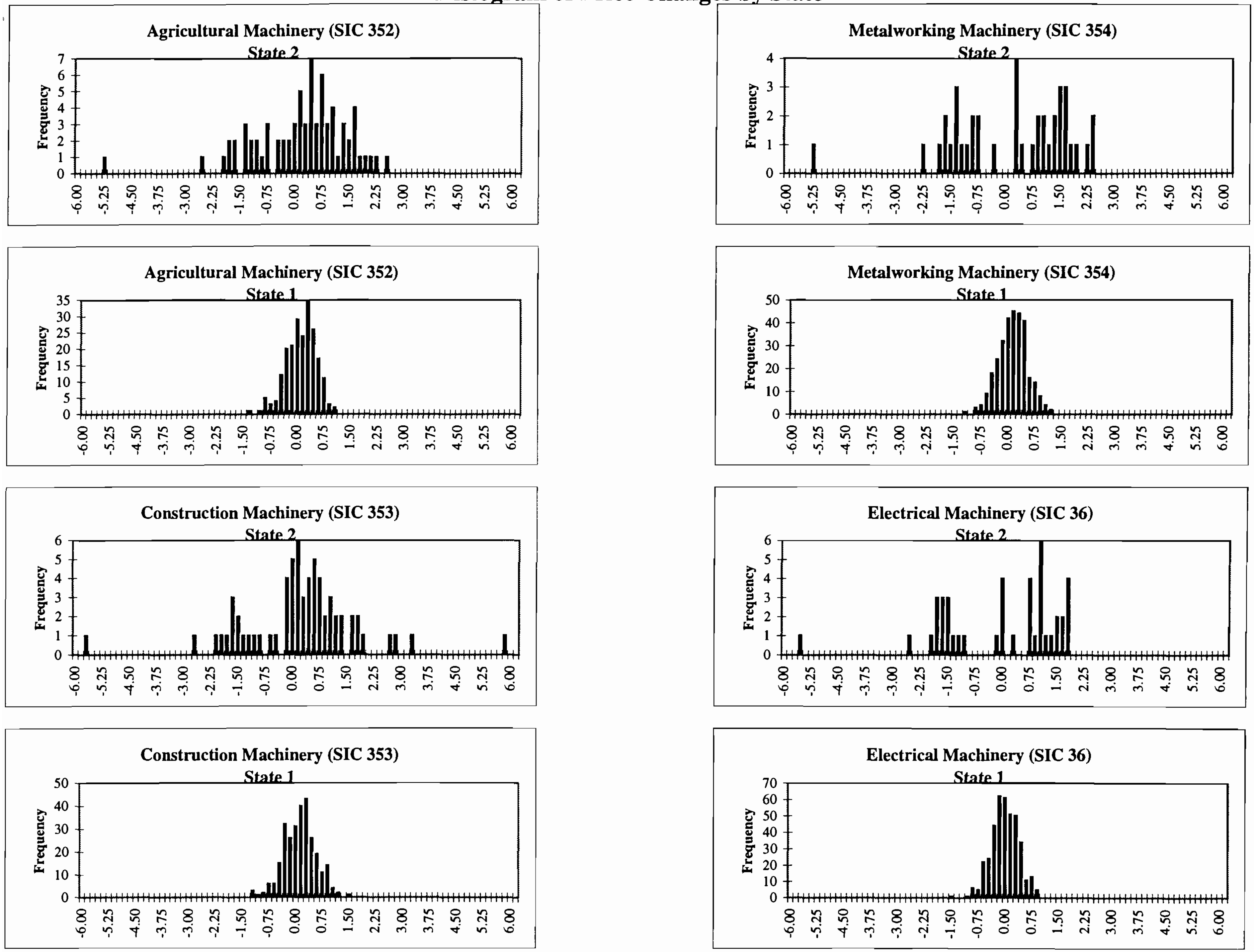


Figure 6e

Histogram of Price Changes by State