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A MICROECONOMIC APPROACH TO PRODUCTION SMOOTHING EMPIRICS

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I. Introduction

Investment is the most volatile part of output, and inventories the most volatile part of investment. The sources of this volatility are badly understood. The most common theory concerns a firm with a stable, rising marginal cost function and desired shipments that vary over time. If the peaks and troughs in shipments can be anticipated, the output inventory of such a firm ought to be chosen to permit production at off-peak, low-marginal cost times. This sounds like an inherently smoothing activity, one that leads to low volatility in production and employment for an inventory-holding firm.

Thus, it is somewhat alarming that studies on aggregate data find that the variance of production over time is larger than that of shipments. Blinder (1986) and West (1986), for example, provide systematic studies of 2-digit industry data. Both reject the "production smoothing model."[1] It is even more alarming that inventory investment does not appear to smooth production at seasonal frequencies. Miron and Zeldes (1988b) find little evidence that 2-digit industries hold inventories to smooth production, even for predictable seasonals. In fact, "in most industries the seasonal in production closely matches the

[1] The phrase "production smoothing model" is a slippery one. The basic components are a convex, nonstochastic cost function and stochastic demand. The model often includes an explicit or implicit assumption of quadratic costs.

seasonal in shipments . . ." (p. 877). It is implausible that seasonal fluctuations in demand are unpredictable, so this appears to be strong evidence against the production smoothing model.

There have been two main lines of response to this puzzle, one model-intensive, the other, data-intensive. It is, of course, not a perfectly general theorem that the variance of production should be smaller than the variance of shipments. The long literature on stochastic, dynamic models of inventory and production (see, e.g. Blanchard (1983)) has provided a general modelling framework for problems of this sort. Within that framework, Eichenbaum (1989) provides one possible explanation of the puzzle, based on marginal costs that are not stable over time. "Production cost smoothing," i.e. producing at times when the entire MC function is low, could easily lead to production being more volatile than shipments.[2] Ramey (1989) examines the possibility of downward-sloping marginal costs, leading to "production bunching" as the dynamic optimum. Both authors have empirical tests in which the "production smoothing" view is rejected against their more general alternative. The stochastic dynamic optimization framework also provides a testing ground for the "production smoothing" view when no specific alternative model is proposed. Miron and Zeldes (1988b), for example, exploit this framework in their seasonal analysis.

The other line of response has emphasized problems with the aggregate data used in these studies. Several studies of disaggregated industries find smoothing. Bresnahan and Suslow (1989) conclude that production-smoothing goes on in the 4-digit industry they study, as does Ghali (1987).[3] Fair (1989) provides a systematic study of seven 4-digit industries for which physical-units output and inventory measures are available, and finds that production smoothing seems plausible in these industries. Fair attributes the failure of more aggregate models to noise in the data. Consistent with that view, Miron and

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[2] Consider, e.g., a French firm which ships the same amount of product every month but for which $Q_{August}=0$.

[3] In Aluminum and Cement, respectively.

Zeldes (1988a) have shown that the industrial production indexes collected by the Federal Reserve Board do not move together with the production series implied by the Commerce Department's manufacturers' shipments and inventories data.

An important recent advance links data improvements with information from another line of inquiry. Pindyck (1990) studies inventories and production in industries for which spot and future commodities prices are available. The excess of the current spot price over futures prices suggests a predictable fall in the marginal cost of production for price-taking industries. For some time we have known that inventory stockouts cause these "backwardations" in commodity prices.[4] Pindyck shows that the high implicit marginal value of inventories near stockouts is also reflected in production behavior. Again, production smoothing appears more plausible in the studies using superior data.

The "bad data" perspective on the production smoothing puzzle leads to some insights about problems with aggregate studies of economic phenomena. A purely data-analytic perspective, however, cannot illuminate the economic forces driving the volatility of production. This paper examines the production and inventory behavior of the ammonia fertilizer industry, a highly seasonal industry with excellent data. Our data will be monthly, industry-wide observations on production and inventory in physical units. As in the earlier studies, using high-quality data immediately makes the production-smoothing model more plausible. Further, we construct a model that reflects the realities of ammonia production and demand. (In this sense, our approach is particularizing and "microeconomic.") In particular, we emphasize:

(A) The shape of the SRMC function.

(B) The nature of shocks to SRMC and demand.

(C) Instruments for the error in forecasts of future demand.

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[4] See Bresnahan and Suslow (1985) and Bresnahan and Spiller (1986).

The use of a model with close ties to the industry's realities will permit uncovering substantially more reliable answers about the dynamics of inventory investment. We show that production does indeed anticipate the forecastable part of seasonal peak shipments. Further, the form of the anticipation varies as we would predict, given our knowledge of the right-angle shape of the SRMC function: when capacity is forecasted to be tight, the industry builds more inventories, and when capacity is not tight, it builds less.

Our econometric modelling effort will focus on (A). In earlier work (Suslow (1986), Bresnahan and Suslow (1989)), we have estimated models of supply with right-angle SRMC. In the present context, some features of these models continue to be useful, especially the steep SRMC around capacity. The earlier models are likely to be too restrictive for ammonia, for which industry MC is not obviously flat out to capacity. First, different firms buy natural gas, the primary input for ammonia production, at many different prices within a single period. Second, it is not obvious that SRMC is vertical, as opposed to steep, near capacity for ammonia, and our model will allow for this.

At the heart of previous empirical work on production smoothing is the classification of the source of shocks to the industry. Are the shocks acting on the demand equation, the cost equation, or both? We would like to take this debate one step further and argue that the form of the shocks to cost matters as well. When the SRMC function has two segments, "horizontal" shocks to cost are different from "vertical" shocks. We have been extremely careful about identifying those things that move the cost function horizontally and dating them accurately. Some of these are forecastable, like capacity expansion. Others are more random, like natural gas curtailments.

II. Production and Shipments in a Precisely-Defined Industry

We chose fertilizer-grade ammonia[5] as the industry for empirical testing of the seasonal production smoothing model because it satisfied several desiderata. First, there were data quality issues.

[5] More precisely, we chose synthetic anhydrous ammonia for fertilizer use, SIC 28731 34.

We wanted inventory data in physical units, rather than financial-based data, for a precisely defined industry. Second, we wanted substantial seasonality in demand. Ammonia is a feedstock for agricultural fertilizer manufacturers, who in turn sell it to farmers. Farmers' use is concentrated in spring and summer. We wanted an industry that was well documented in the public domain, so that we could research the relevant issues about forecastable determinants of demand and the shape of SRMC. Finally, we wanted an industry inside the six two-digit aggregate industries most often studied in the literature.[6]

We will describe the data precisely below. For now, let us concentrate on the seasonals. Figure 4 and Table 1 report the results of regressing ammonia production, Q, and shipments, S, on a set of monthly dummies and time. The sample runs from July 1974 through June 1988. We define the seasonals as the predicted values of the regression for each month at the mean of all the other regressors.[7] This procedure leads to seasonals whose means are the same as the means of the underlying monthly data. Also, the sums of the production and shipments seasonals are the same to three decimal places. Thus, we can interpret any difference in the patterns of these two series as reflecting seasonal factors. The numerical values of the seasonals are shown in Table 1 and graphed in Figure 4. In the figure, we first see that shipments have a much more pronounced seasonal than production. The two series correspond in March; after that, shipments are well over production for the next two months, and slightly over in June. For the rest of the year, predicted production is slightly over predicted shipments.

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6 The bulk of the studies referred to in the introduction have been carried out on two-digit manufacturing industries. Some use all industries, others concentrate on the six industries identified by Belsley (1969) as "produce to stock." The use of two-digit data is inherently suspect. What is the output inventory of a two-digit industry? The answer to the data question is clear. It is the sum of the output inventory of all the firms in the industry. Yet most two-digit industries contain very substantial shipments from upstream narrowly-defined industries to downstream ones. For example, ammonia for fertilizer is overwhelmingly shipped to fertilizer plants; they, too, are inside SIC 28 (chemicals).

7 This regression is closely related to "detrending." The seasonals implied by a more complex regression, with agricultural demand variables such as the corn and wheat harvest included, are very similar.

There are two things to note about Figure 4. First, production has a much smoother seasonal than shipments. There is clear evidence of seasonal production smoothing just in this simple graph. It seems likely that we will end up agreeing with the earlier studies using good data; reliance on too-aggregate, financially-based data are an important cause of the common finding that production smoothing does not occur. Second, the peak of production and the peak of shipments come at the same month; this is the same fact noted by Miron and Zeldes. Sensibly, they took this as evidence against a simple dynamically-optimizing theory of production smoothing. If production planning by firms recognizes the peak in shipments, should not the peak in production be broader and partially lead the peak in shipments? That it does not is a puzzle we will need to explore in some depth.

III. Disequilibrium Model of Production

Figure 1 depicts a short-run marginal cost (SRMC) function appropriate for some capital-intensive, flow-process industries. There is a fixed stock of capital, which defines capacity for the industry. In the figure, we have drawn capacity as a fixed constraint, so that SRMC is vertical at K. As we shall see, it is not critical that the second portion is vertical. Two things <u>are</u> critical. The first is that plant is a fixed asset in the relevant run. The second is a marked change in the slope of SRMC around capacity, so that it is much steeper at higher levels of production.

The figure also can serve to fix our framework of analysis. The definition of "SR" in SRMC is the run in which one can take as fixed both the average variable cost (AVC) function below capacity, determined by the level of technology, and the level of economically available capacity (EK), determined by the amount and type of plant and equipment. Our approach will take capacity, factor prices, and technology to be econometrically exogenous in monthly data. Further, we take capital to be completely fixed, and all other factors to be completely variable. In the short-run, AVC is thus given by the input requirement for variable factors.

How is cost-minimizing production determined in an industry with technology of this shape? There are two reasons to produce; current shipments and building inventory for future shipments. Let us leave the dynamic part of the story in the dark for the moment, and assume that there is a well-defined "benefit function" for production at the current time,

$$B(Q_t; S_t, I_t, X_t) \equiv \max_{S_t, Q_\tau, S_\tau} \Pi_t(Q_t, S_t, I_t, X_t) + E\left[PDV(\Pi_\tau(Q_\tau, S_\tau, I_\tau, X_\tau) \mid X_t\right]$$

where X_t represents exogenous variables and future endogenous variables are denoted with a subscript τ. The X's can affect the benefit of current shipments, or they can predict the benefit of future shipments; thus, they likely include all variables shifting demand or cost. The intersection of the derivative of the benefit function, $MB(Q_t; S_t, I_t, X_t)$, and SRMC determines optimal quantity in each particular period. For the rest of the discussion, we will drop the time subscript and suppress the arguments of MB(Q) other than Q.

Figure 1 shows a downward-sloping marginal benefit function, MB(Q). Let Q_1^* be the intersection of MB(Q) with AVC. The interpretation of Q_1^* is as "desired" production ignoring the capacity constraint. One regime arises when the intersection of MB and AVC occurs past capacity. Then $Q_1^* \geq EK$, and the industry produces at capacity: $Q = EK$. When $Q_1^* < EK$, then $Q = Q_1^*$.

We add covariates, X, that shift MB (either currently or by predicting the future) or MC to Q_1^*. We also add econometric errors. The result is an econometric model of "disequilibrium" (short-side-wins). See Quandt (1988). Regime 1 specifies "desired" production, Q_1^*. Regime 2 specifies capacity.

If we let β_1 be unknown parameters, this leads to a two-regime model:

Regime 1: $\quad Q_1^* = X\beta_1 + e_1$

Regime 2: $\quad Q^c = EK + e_2$

and $\quad Q = \min(Q_1^*, Q^c)$,

where Q_1^* is the intersection of MB( ) and AVC in Figure 1 and Q^c is the quantity produced when the capacity constraint is binding. We estimate this model by maximum likelihood under the assumption that e_1 and e_2 are independent and normal. The likelihood function is the product of densities given by:

$$h(Q_t) = f(Q_t - X\beta_1, s_1)\left(1 - F\left(\frac{Q_t - EK}{s_2}\right)\right) + f(Q_t - EK, s_2)\left(1 - F\left(\frac{Q_t - X\beta_1}{s_1}\right)\right),$$

where f( ) is the normal density function and F( ) the cumulative.

Weakening the Technological Assumptions

Plant capacity may be fixed in the short run yet not provide an absolute barrier to higher levels of production. Producing at 105 percent of rated capacity probably involves extra costs, such as extraordinary maintenance ("fixing it with the motor running") but is well within normal operations practice in many industries. In Figure 3, we diagram a simple model that captures this possibility. Out to capacity, K, marginal cost has slope c_1. Beyond capacity, it has slope c_2. Suppose that the marginal benefit schedule for production from the producers' long run problem can be either of the A type or the A' type, as shown in Figure 1. How will this model differ from the earlier one with flat SRMC out to K and vertical SRMC thereafter?

The solution is straightforward. The equation for Q_1^* is:

$$A - b\, Q_1^* = c_0 + c_1\, Q_1^*.$$

Assuming that random influences and observable covariates, X, shift the slopes and intercepts, let the solution to this equation take the form:

Regime 1: $Q_1^* = X\beta_1$.

(We reuse the $X\beta_1$ notation because regime 1 is the same in the two models.) Now, when $Q_1^* > EK$, Q is not equal to Q_1^*. Instead, the equation for Q^c is

$$A - b\, Q^c = c_0 + c_1\, K + c_2\, (Q^c - K).$$

It is easy to see that the solution is:

Regime 2: $Q^c = w_1X\beta_1 + (1-w_1)\ K$,

where $0 < w_1 = (b+c_1)/(b+c_2) < 1$. Thus, the intuition of the model is clear. There is the additional "weight" parameter, w_1, which measures how much less responsive quantity is to movements in demand and cost in the second regime. With a vertical capacity constraint, it is not responsive at all. As the capacity constraint steepens, w_1 falls, and Q^c becomes less responsive to exogenous shifts compared to Q_1^*.

Again, we add errors in both regimes and estimate by maximum likelihood.

A Very Simple Dynamical Model

A model of EK is largely based on the interface between engineering, operations research, and economics. But what about a model for $X\beta_1$? We base ours in the cost-minimization problem of the firm. Given shipments now and expectations about shipments in the future, the firm decides how much to produce.

The stochastic dynamic program involved in cost-minimizing production for a given pattern of shipments over time is quite complex. We base our model of the determinants of the MB( ) function on observations about the nature of the solution in the certainty case. While this leaves some aspects of the production smoothing model untested, it has several advantages. First, it is "close to the data"; we will be able to say what the descriptive evidence for the hypothesis is in a straightforward way. Also, this approach does not need many assumptions about the stochastic process driving shipments.

The solution in the deterministic case can be described with three simple production scheduling questions for a hypothetical Christmas-card producer who has to ship one million units on October first, and who has flat MC out to vertical capacity. Question 1: You have 0.5 million units of capacity/month.

What do you do? Answer: Start production on August 1.[8] The solution is to start producing as late as possible, given the production goal. To make the cards earlier is wasteful of interest cost. Question 2: Now, in addition, you have orders for shipments of 0.25 million units on September 1. What now? Answer: In August, I should produce the 0.25 million units to ship at the end of the month. I now need to start to build for October 1 in the last week of July. Question 3: Vacations in August systematically reduce capacity in that month by one-fourth. What now? Answer: Now I need to start up production on July 15th to make both shipments.

In general, the solution to a deterministic, flat MC to capacity, capacity constrained production problem with a single seasonal peak has the following solution. Let t be the current period, and let T be the end of the marketing year. Calculate the capacity shortfall for the rest of the year as follows: First, the amount of shipments needed after the current period are:

$$S_{needed} = \Sigma^{T}_{\tau=t+1} S_{\tau}.$$

Second, the amount of capacity available to meet those shipments is:

$$K_{available} = \Sigma^{T}_{\tau=t+1} K_{\tau}.$$

Third, there may already be inventory in hand from previous production. There also may be some level of inventory that is needed simply to "service" the shipments at the peak, $\underline{I}_T$. Thus, the net inventory available to meet the needed shipments is:

$$I_{available} = I_t - \underline{I}_T.$$

Thus, the measure of tightness of capacity or capacity shortfall appropriate to the deterministic case is:

$$\text{Shortfall} = S_{needed} - K_{available} - I_{available}.$$

The optimal plan in a pre-peak period is to produce enough to meet current shipments and then, if shortfall is positive, to produce further units up to shortfall.

[8] The buried assumption is that the kink is adequately sharp that it is not worth it to produce substantially much up the steeper portion on the last day of September, thereby saving interest charges from the first of August.

For our empirical model, we will use the future realization of "shortfall" and the current value of shipments in the equation for desired (regime-1) production. Each enters $X\beta_1$ with an arbitrary coefficient. Since the future realization of shortfall equals the firm's expectation about it plus error, we will need to treat this measurement error problem.

IV. Ammonia Fertilizer Industry Background and Data

Industry Definition, Output and Structure. Ammonia for fertilizer is produced by chemical manufacturers of fertilizer and fertilizer feedstocks. Ammonia for non-fertilizer uses is a smaller industry, and the capacity to produce the two varieties is evidently not fungible. Hereafter, we will use "ammonia" to stand for the fertilizer feedstock only.

The ammonia industry itself is not very concentrated, involving 58 firms and 87 plants in 1982.[9] We will treat the ammonia industry as competitive. In particular, we will assume that the pattern of production across plants within the entire industry is cost minimizing.

Current Industrial Reports. "Inorganic Chemicals" publishes monthly data on total U.S. production and stocks of inventory for the ammonia fertilizer industry. The production data is separated into "ammonia for fertilizer" and "ammonia for other uses," which accounts for about ten percent of total ammonia production. (See Table 2 for a list of brief variable definitions, units, and sample means.) Our shipments variable is derived from the production and inventory data. The data run from July 1974 through June 1988.[10]

[9] The downstream fertilizer industry, consisting of manufacturers' agents and dealers who sell the fertilizer to farmers, is fairly concentrated. Markham [1958], among others, suspected that there was substantial market power in the downstream segment.

[10] Price controls were lifted for fertilizer in late 1973, suggesting a regime change. Our specification is such that we prefer to use entire fertilizer marketing years, ending in June, rather than calendar years.

Technology and Cost. Ammonia is made in large-scale, continuous flow facilities. The main inputs are natural gas and capital. At the natural gas prices obtaining at the beginning of our sample, U.N. analysts estimated natural gas' share in the costs of a best-practice plant at just over 40.5 percent, with capital's share just under 40.5 percent.[11] Opportunities to substitute out of the energy input have been limited, so the share of natural gas in cost has risen and fallen with the price of fuel. Natural gas contracts vary somewhat in length, so that different plants obtain fuel at different costs. As of June, 1982, for example, 19 percent of the industry obtained natural gas at prices under $\$1.50/cf*10^6$, while 24 percent were paying $\$3.50/cf*10^6$ or more.[12] Other materials, management, and indirect labor make up much of the rest of cost; direct labor is primarily important in the maintenance function.

The shape of industry SRMC below capacity reflects heterogeneity across plants. Within any particular plant, the technology makes AVC fairly flat. In principle, there are two sources of heterogeneity across plants; technological and input-price. Technological heterogeneity arises because the plants are of different vintages and scales. Within our sample period, there is more variety early than late; the contraction of industry capacity in the early 1980s removed the oldest plants. It appears, however, that the technological heterogeneity contributes primarily to interplant variation in capital cost, not to variation in AVC. The natural gas requirements per unit output for different scales and vintages of plants appear to be roughly the same. Input price variation is a much more important source of slope to the industry AVC. The terms on which the firms in the industry obtain natural gas vary widely, from spot-market purchase out to very long-term contracts. As a result, the rise and then fall of energy prices over the sample period induces shifts in industry SRMC, as those firms that buy in the spot market have costs that move more than others. As a result, the slope as well as the level of SRMC might vary over time.

[11] See United Nations (1980), Table 6, p. 67.

[12] See Table 4 in "U.S. Ammonia Producers hit by high costs, slack demand," G. Alan Petzel, in the May 16, 1983, Oil and Gas Journal.

To investigate this problem, we examined the distribution of natural gas prices in the industry at the peak of real energy prices in 1982. Petzel (1983) reports the fraction of industry plants falling in price bunches that are $0.50 wide, from under $0.50/million cubic feet up to $4.00/million cubic feet. These are graphed in Figure 5. It may not be obvious that the graph has seven kinks; it appears to be piecewise linear with a split at 34 percent. The important nonlinearity in the industry SRMC below capacity clearly appears at that point. The industry's capacity utilization never gets below 50 percent in our sample. Thus, the part of SRMC that is relevant to the econometric analysis is to the right of the sharp kink. The right assumption appears to be that SRMC is approximately linear but not horizontal. It has a slight slope in the relevant range.

The ammonia process fits well within the disequilibrium (capacity) model. The rate of production is fixed by the capacity of the plant itself. Plants are typically operated on a 24 hours/day, 7 days/week basis when they are up.[13] There is both an "idle" state, from which the plant can easily return to operation, and a "shut down" state, from which return is somewhat more difficult. The production planning decision at the plant level is when to be operating. At the industry level, it is what fraction of the plants are operating. The rated capacity of a plant in operation assumes a 340-day operating year, with scheduled maintenance downtime at the end of the peak (Spring) season. Operating rates over and under 100 percent of rated capacity are not uncommon, as maintenance tasks can be deferred or done in a more expensive way to keep the plant operating. It is not obvious how important these decisions are, so we chose to use the sloping-capacity constraint version of Figure 3 to capture the possibility that the economic maintenance decision is of some importance.

Our basic capacity data come from the Tennessee Valley Authority's publication "Fertilizer Trends." This bi-annual (roughly) publication lists capacity, by plant, for anhydrous ammonia producers

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[13] The ammonia production process requires high temperatures, so that cool downs and shut downs are expensive. Therefore, managers prefer to run the plant 24 hours/day, 7 days/week.

in the United States. It also shows the status of each plant: operating, idle, closed, under construction, expanding, and so on. The capacity series we use represents the total of all operating and idled capacity. We subtract ammonia production for other uses from this total capacity figure to arrive at capacity for fertilizer usage.

One problem with the biannual capacity data concerns the exact timing of plant openings and closings. To improve on the published data, we made several phone calls to the ammonia producing companies. Company representatives often told us when the plant opened or closed. We changed the capacity series accordingly.

A second problem arises only in the most recent years of the data. When a plant is "retrofitted" with newer capital equipment involving superior technology, the TVA increases its estimate of the plant's capacity. Industry sources report that in the last few years many plants have been retrofitted. Because these retrofits are recent, the TVA data may not yet reflect them. Therefore, it is not obvious that nameplate capacity figures are accurate at the end of the sample. We handle this problem by adding dummy variables for 1987 and 1988 in the capacity equation.[14]

The final source of horizontal cost shocks was the natural gas shortages of the regulatory era. Our sample begins in July 1974, while interstate natural gas prices were under federal government control. From the beginning of our sample through 1978, shortages of natural gas occurred throughout the nation. Industrial users suffered "curtailments."[15] Many ammonia plants experienced cutbacks in natural gas supplies during the winter months.[16] The winter of 1976/77 was abnormally cold, creating a "gas crisis."

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[14] We are grateful to two industry sources, Ed Harre, Tennessee Valley Authority, and Rick Strait, M.W. Kellog Company, for many useful conversations about the capacity measurement problems.

[15] Residential and small commercial users rated a Federal Power Commission priority of 1, while ammonia manufacturers rated a priority of 2 or lower. (Hydrocarbon Processing, Nov. 1976, p. 97.)

[16] The ammonia industry is concentrated in Louisiana and Texas, making it particularly susceptible to regional shortages. In 1981, for example, the West South Central region accounted for roughly 54% of total U.S. ammonia production. (Current Industrial Reports, 1981, Inorganic Chemicals, Table 6.)

The crisis subsided in the 1980s after natural gas price decontrol. The trade literature throughout the 1980s consistently speaks of a natural gas surplus or "bubble." Regional shortages occurred on occasion due to extremely cold weather, but overall supply was more than adequate to satisfy residential and industrial demand.

These shocks to capacity were not trivial. Between December 1976 and January 1977, for example, the ratio of production over nameplate capacity falls from .92 to .62. The trade press of that time is full of stories about plant shutdowns due to curtailments. Accordingly, we add another variable, total natural gas curtailments for the year, to our capacity equation in January and February with an arbitrary coefficient.

Demand. Fertilizer demand depends on farm incomes, weather conditions, and government price support and acreage reduction programs. Within our sample period, there have been several major shifts in U. S. farm policy. The US-USSR grain agreement went into effect October 1985. Major farm bills passed in 1973, 1977, 1981, and 1985. Congress passed the payment-in-kind program at the beginning of 1983. PIK severely restricted the number of acres planted and had a major impact on the size of the agricultural sector. (An index of total feed grain output fell by 45 percent in 1983.[17]) According to industry reports, while the average application rates of fertilizer per acre have remained about the same since the early 1980s, total fertilizer use has declined because of fewer acres planted of major crops.[18]

Our data are monthly. For econometric purposes, our unit of analysis is a "fertilizer marketing year," which ends with June.[19] Demand is highly seasonal, as can be seen in Figure 4. The ammonia marketing year is geared toward a spring planting season for farmers. Much of the uncertainty about

[17] Agricultural Statistics, USDA 1988, Table 560.

[18] Fertilizer summary data, TVA 1988, p. 5.

[19] In this, we follow the convention of Current Industrial Reports.

demand is resolved in the winter and the spring. In summer and early autumn there is always sufficient capacity to cover current demand.

Since our model is one of cost minimization, we will need demand-side instruments. For example, the future value of shipments over the rest of the year is a critical datum for ammonia producers. The realization of shipments is presumably an error-ridden proxy for producers' expectations. What is an appropriate instrument? At least half the ammonia fertilizer used goes into corn production. The Department of Agriculture publishes quarterly forecasts of corn production, planted acres, and acres harvested for each upcoming marketing year. We use the forecasted corn production figures as instruments for predicting ammonia for fertilizer shipments. As a result, only the anticipated part of future shipments affects current Q in our specification. These forecasts are updated throughout the year and may apply to decisions to be made for the current marketing year (in February, for example) or the upcoming marketing year (after September).

V. Empirical Specification and Results

Our empirical specification has the following variables in $X\beta_1$: a constant, 3 quarterly dummies, current shipments times 4 calendar quarter dummies, and shortfall times 4 calendar quarter dummies. Our specification for EK has nameplate capacity, dummies for 1987 and 1988, and the curtailment variable described above. The instrument for shortfall is the USDA corn production forecast for the relevant marketing year. The model is just-identified when shortfall is treated as observed with error.[20] Descriptive statistics on these data are in Table 2.

Table 3 presents estimates of the disequilibrium supply model. The parameter w_1 is near zero; apparently the view of the capacity constraint as essentially vertical is correct. The change in the slope

[20] The reduced-form regression for shortfall fits much better if dummy variables for the major farm policy actions are included. But we thought that it would be overfitting the prediction equation by including them as instruments.

of the marginal cost curve comes at approximately 0.85 times nameplate capacity; the difference is normal maintenance and downtime. The year dummies and the curtailment variable have the anticipated signs and orders of magnitude.

The size and variation of the coefficients of current shipments suggest that the simple model works well. In the summer and fall, far in advance of the peak, the industry's production planning rule appears to be "produce to ship." At that time, current shipments have a coefficient of one and future shortfall has a coefficient of zero. For the winter and spring, inventory investment is much more important as a determinant of production. The shortfall variables for these quarters before and during the peak are large and positive. It appears that, as the peak approaches, the forward-looking policy suggested above is in place. Accordingly, the coefficient on current shipments falls well below one for these quarters.

The coefficients also have a reminder that we have left stochastic elements out of the model. Predicted production is positive and rising over the marketing year even if current shipments and shortfall are zero. Clearly this reflects the building of "safety stocks" which the deterministic model cannot capture in any other way.

Some idea of the fit of the model and of the meaning of the coefficients in $X\beta_1$ can be obtained by looking at Figure 6. It shows actual production, Q, as well as Q_1^* and Q^c. (Of course, given our estimate of w_1, Q^c is close to EK.) At the bottom of the figure, we provide upward-sloping lines that show what month it is.

Note that Q_1^* is much more volatile than production itself. (To make the figure manageable, we have truncated the larger Q_1^*s.) Only in the periods of ongoing excess capacity--for example, see the 1982/1983 agricultural crash--do production and Q_1^* move together over the entire year. More typical is the pattern in which production is truncated above by capacity at the seasonal peak. Thus, the simple seasonal of actual production shown in Figure 4 and Table 1 is an average of the untruncated (highly seasonal) and truncated (essentially aseasonal) series.

Figure 7 graphs the seasonals of $X\beta_1$, which illuminate this point.[21] The X-axis here corresponds to a marketing year, so that June is labelled 12 and July labelled 1. The mean of $X\beta_1$ is clearly above the mean of shipments, as one would expect.[22] In looking at the figure, it is helpful to remember what concept, Q_1^*, lies behind $X\beta_1$. Q_1^* is not the prediction of the model under the assumption that the capacity constraint never binds. Instead, the capacity constraint is relaxed for this period only, but the likelihood that it will bind in the future remains the same. What happens? In the last quarter of the marketing year, Q_1^* = shipments. The logic is obvious; when there is no future, produce to demand. In month 6 through 9, Q_1^* is much greater than shipments. This is production in anticipation of the coming peak. Earlier, Q_1^* is only slightly above shipments; there is not much of a production smoothing motive at that long remove.[23] Of course, the farther one goes to the right in the diagram, the greater the likelihood the capacity constraint will bind and Q_1^* will not determine actual production.

Generality of the results. We have argued that using particular assumptions about ammonia production was an important part of our method. These assumptions are grounded in the engineering and economic analysis of the industry. How general are the results, given this particularizing agenda?

There is a large class of industries that have capital intensive facilities where capacity adjusts slowly and is long-lived. For these industries it is reasonable that SRMC increases rapidly around K. Within this class of industries, we would expect to get the same findings as here: There is substantial production smoothing, not easily detectable given the maintained hypothesis of standard Euler-equation approaches.

[21] The seasonals for $X\beta_1$ were calculated by the same procedure used for Q and S.

[22] The means of Q and S are identical, and $E[X\beta_1] > E[Q]$ in the disequilibrium model if the capacity constraint binds with positive probability.

[23] Though the persistence of $Q_1^* > S$ even here reminds us that we have left uncertainty out of our treatment. There is surely some "safety" stock building going on here.

VI. Conclusion: Production Smoothing and Inventory Investment

What does a simple deterministic model of capacity-constrained production smoothing say about inventory investment? There are two implications. The first is a tendency for inventories to be built in anticipation of the seasonal peak. As the "shortfall" covariate suggests, the efficient policy in the certainty case is to build inventory as late as possible before the peak. The second implication uses the kink in SRMC in a different way. It contrasts years in which there is pressure on capacity with years of generally loose capacity. Contrasting patterns in production and shipments are presented in a heuristic fashion in Figure 2. First, imagine a producer making production decisions for a particularly low demand year, and call this a type "2" year. Then, the optimal plan is to produce for demand. Figure 2 shows that for a low demand year S2 is well below K, so S2 and Q2 move together. Production will always be far below capacity. Now take the same decision in a peak demand year. The plant will run at close to full capacity for the entire year, with inventories set aside in anticipation of the peak season for shipments. (See Q1 and S1.) Thus, there are some years when there is a reason to smooth production, and other years when there is not. The testable empirical implication of this observation is that years with forecastable tight capacity should see more inventory investment than other years. When there is little pressure on capacity, inventories can be small. When there is considerable pressure on capacity, inventories need to be larger.

We examined the predicted values of "shortfall" in the ancillary regression. These tell us at what times the model says that capacity could reasonably be anticipated to be tight or loose. We focussed our attention on the six pre-peak months of autumn and winter. The data clearly divided into two very distinct types; the years 1977, 1978, 1982, and 1983 were clearly ones of capacity looseness; forecasted shipments were low relative to forecasted capacity and inventories as of the fall and winter. The other years, except for an ambiguous 1985, were clearly times of much greater capacity tightness. We lumped 1985 in with the tight years and made Figure 8.

The figure shows the seasonals for inventories divided by the seasonals for sales for each of the two subsamples.[24] The lines roughly correspond at the end of the marketing year; whether capacity has been tight or loose, the industry holds under one month's inventory after the April/May/June peak. Both lines also have a substantial pre-peak bulge. Inventories are clearly being built in anticipation of the peak. The lines basically differ in their height. In those years when it is reasonable to forecast that capacity will be tight, substantially higher inventory investment occurs. Thus, both of the idiosyncratic implications of the capacity-constrained production smoothing theory are clearly visible in the data.

[24] The seasonals were calculated as above.

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TABLE 1

Seasonals for Production and Shipments

Regression for q

Degrees of freedom:	160
R-squared:	0.175
Residual SS:	3.181

Variable	Estimate	Standard Error
YEAR	-0.004792	0.002577
JAN	1.574818	0.213408
FEB	1.622238	0.211917
MAR	1.692412	0.211917
APR	1.736052	0.211917
MAY	1.685578	0.211917
JUN	1.627298	0.211917
JUL	1.535945	0.210872
AUG	1.561552	0.210872
SEP	1.561690	0.210872
OCT	1.572623	0.210872
NOV	1.611672	0.210872
DEC	1.652891	0.210872

Regression for s

Degrees of freedom:	160
R-squared:	0.714
Residual SS:	6.436

Variable	Estimate	Standard Error
YEAR	-0.001302	0.003666
JAN	1.066681	0.303579
FEB	1.147239	0.301457
MAR	1.406341	0.301457
APR	2.154536	0.301457
MAY	1.696663	0.301457
JUN	1.457060	0.301457
JUL	1.135334	0.299970
AUG	1.168936	0.299970
SEP	1.173761	0.299970
OCT	1.168299	0.299970
NOV	1.245348	0.299970
DEC	1.169322	0.299970

Seasonals

q	s
1.1875995	0.9615079
1.2350195	1.0420661
1.3051938	1.3011676
1.3488334	2.0493624
1.2983591	1.5914894
1.2400797	1.3518865
1.1487260	1.0301608
1.1743335	1.0637631
1.1744716	1.0685879
1.1854048	1.0631254
1.2244538	1.1401746
1.2656725	1.0641486

TABLE 2

Descriptive Statistics

Variable	Mean	Definition	Units*
Q	1.233	Production of ammonia for fertilizer	short tons (10^6)
I	1.726	Inventories of ammonia for fertilizer	short tons (10^6)
S	1.231	Shipments of ammonia for fertilizer	short tons (10^6)
K	1.532	Ammonia capacity	short tons (10^6)
QOTHER	0.138	Production of ammonia for non-fertilizer	short tons (10^6)
curtail	0.162	Annual natural gas curtailments x dummy for January/February	cubic feet (10^9)
y87	0.071	1987 dummy	(0,1)
y88	0.036	1988 dummy	(0,1)
YEAR	81.000	year	--
MONTH	6.500	month	--
s_left	7.454	sales left in mkt. year	short tons (10^6)
k_left	8.457	capacity left in mkt. year	short tons (10^6)
short	-1.375	supply shortfall (mkt. yr.)	short tons (10^6)
short1	-0.323	short*(1st calendar qtr.)	short tons (10^6)
short2	-0.314	short*(2nd calendar qtr.)	short tons (10^6)
short3	-0.453	short*(3rd calendar qtr.)	short tons (10^6)
short4	-0.385	short*(4th calendar qtr.)	short tons (10^6)
cforc	6848.580	corn production forecast	bushels (10^6)
CORN	0.687	harvested acreage of corn	acres (10^9)
WHEAT	0.630	harvested acreage of wheat	1000S acres
JAN	0.083		
...		month dummies	(0,1)
DEC	0.083		

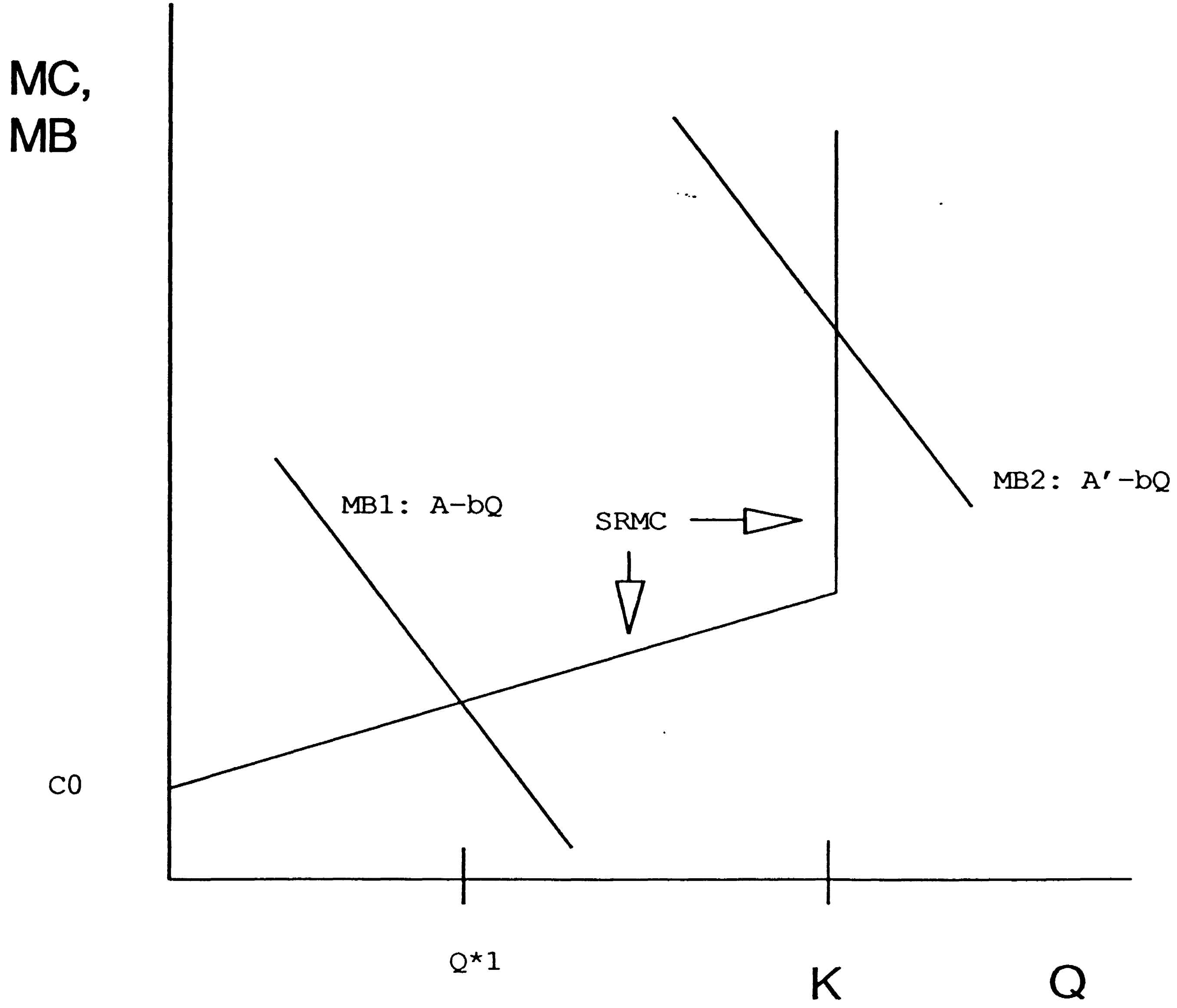
TABLE 3

Disequilibrium Model Estimates

Parameter	Estimate (Standard Error)		
constant	0.380 (0.168)		
winter	0.673 (0.485)		
spring	0.784 (0.255)		
summer	-0.198 (0.277)		
sales (winter)	0.559 (0.311)		
sales (spring)	0.559 (0.116)		
sales (summer)	0.953 (0.185)		
sales (autumn)	0.881 (0.153)		
short (winter)	0.197 (0.103)		
short (spring)	0.477 (0.110)		
short (summer)	-0.007 (0.022)		
short (autumn)	0.025 (0.031)		
k	0.848 (0.016)		
y87	0.061 (0.028)		
y88	0.171 (0.075)		
curtail	-0.065 (0.011)		
$h(w_1)$	1.978 (0.479)	w_1:	0.121566
$g(s_1)$	-2.220 (0.135)		
$g(s_2)$	-2.748 (0.113)		

Standard errors computed from outer product of gradient.
Likelihood Function: 197.044

Optimal Quantity with Capacity Constraints



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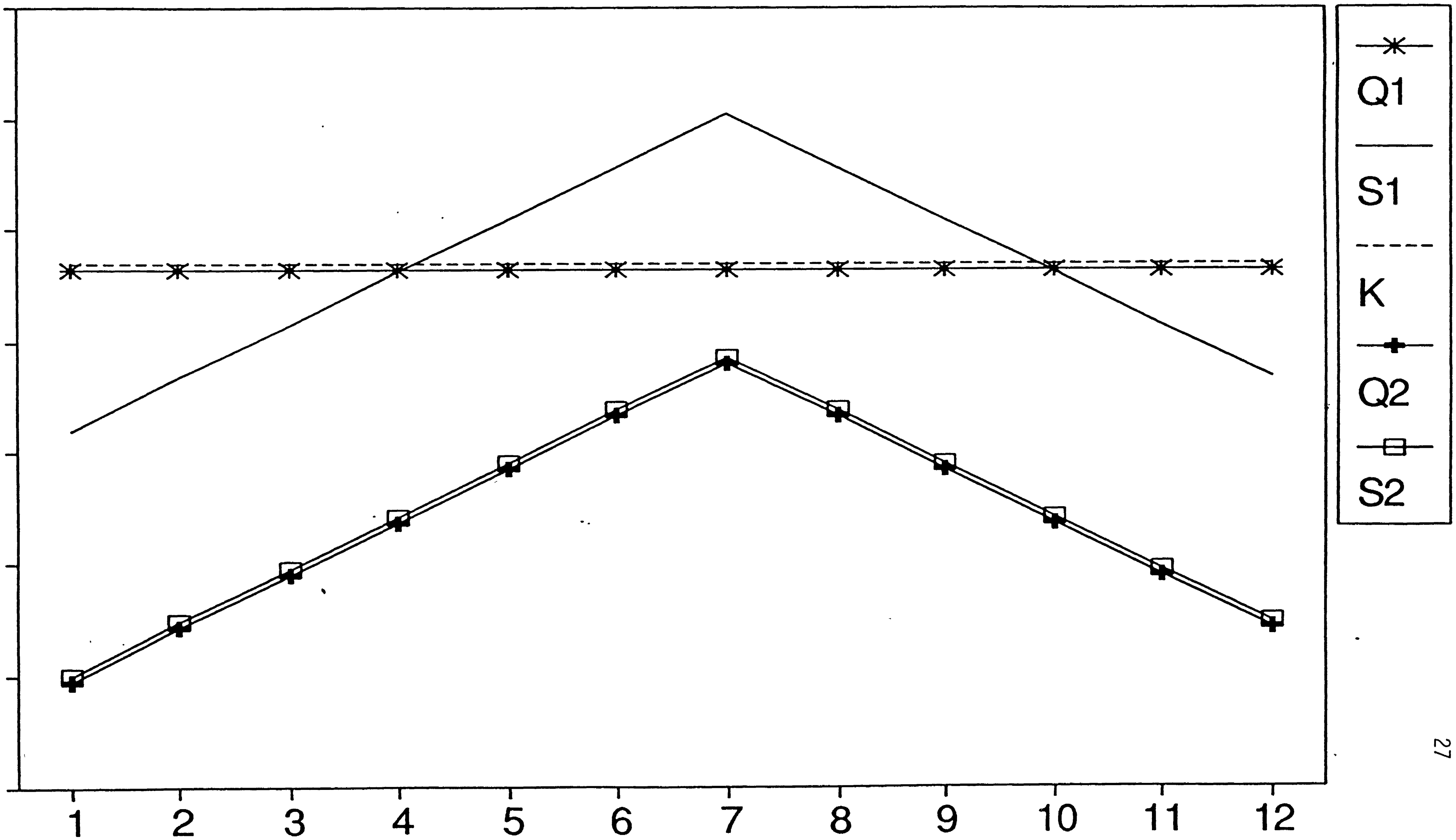
Capacity, Shipments, and Production

In Two Perfect-Foresight Environments



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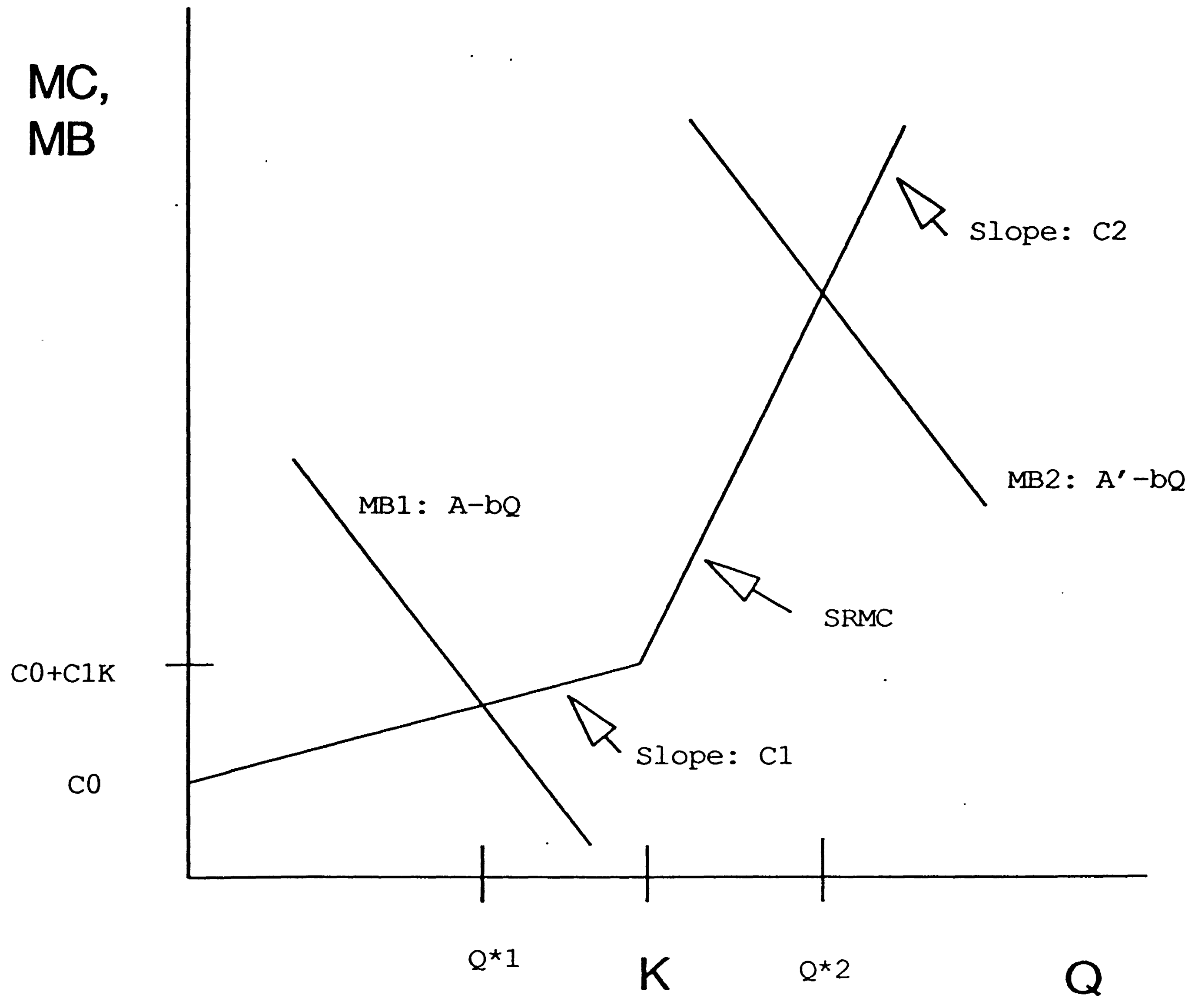
Production Quantity Determination



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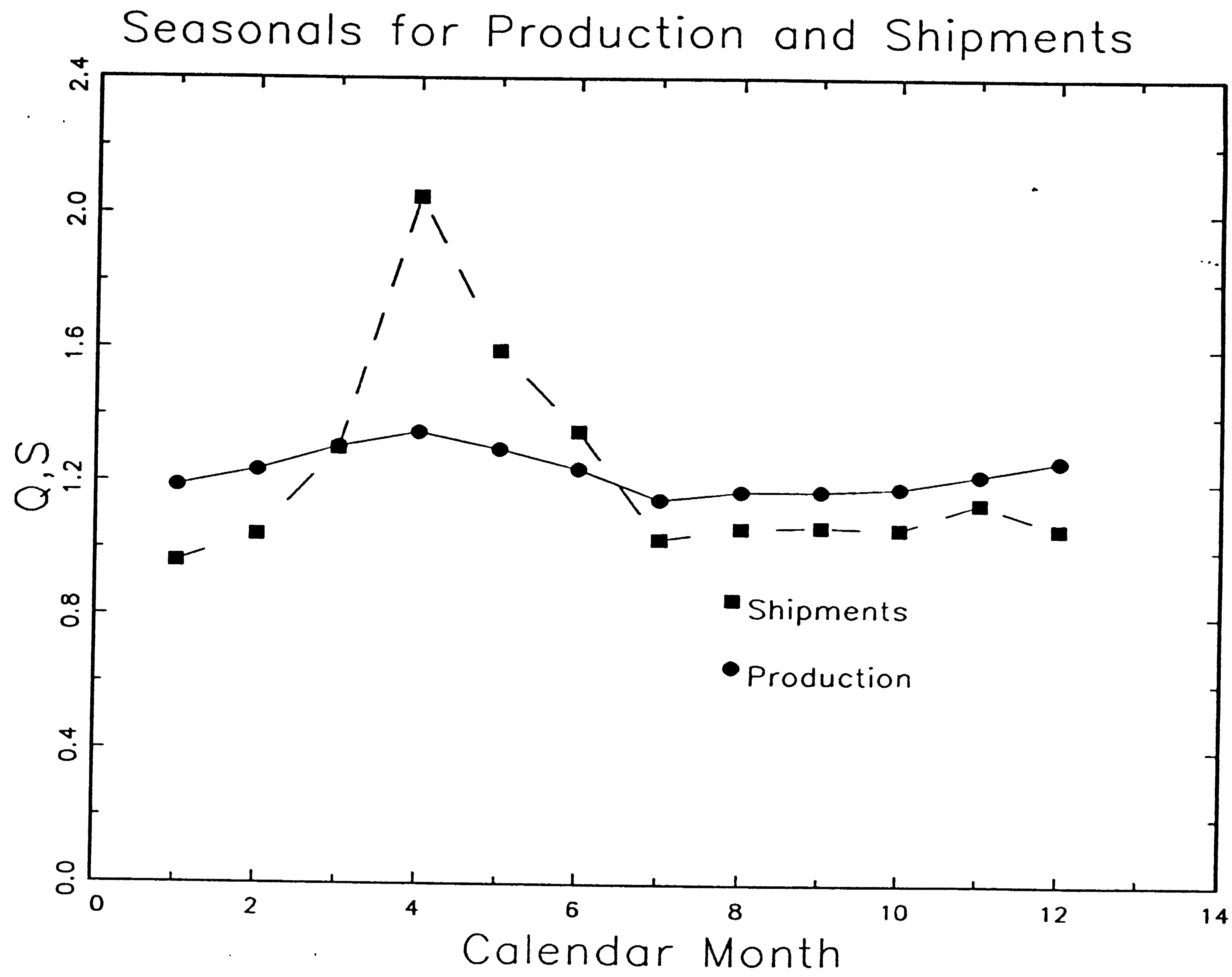

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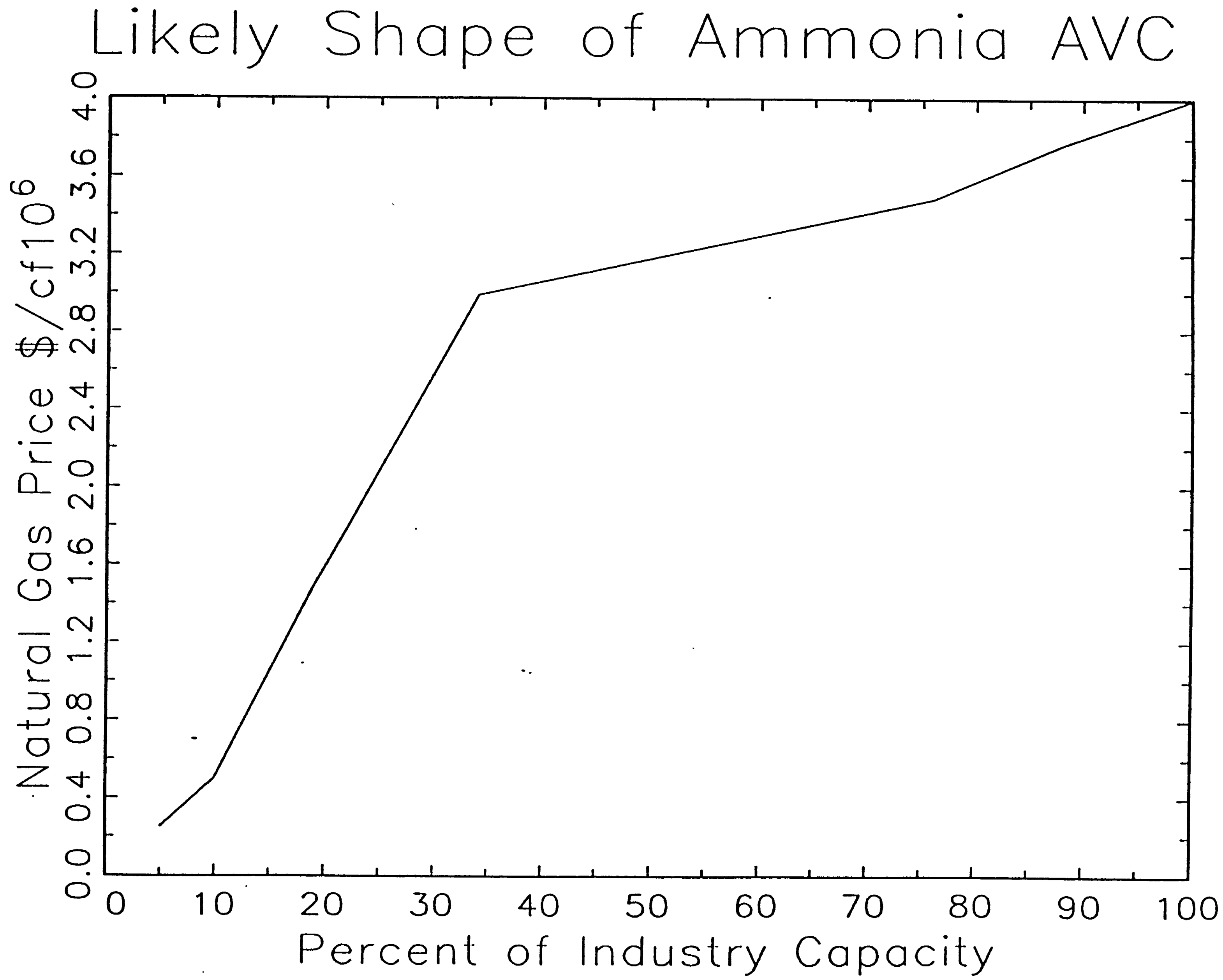

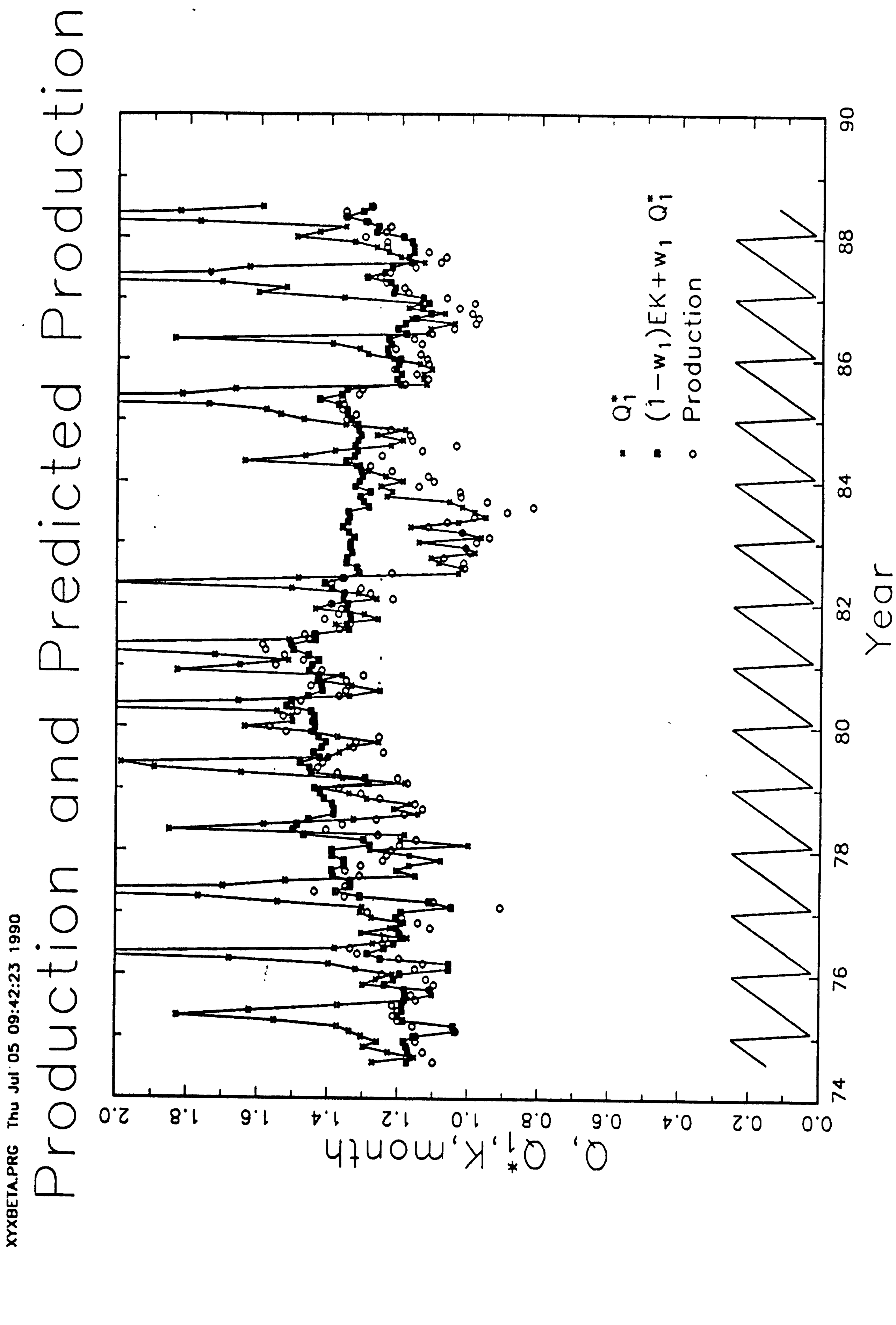
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Production and Predicted Production
Q, Q*1, K, month
Year
Q*1
(1−w1)EK+w1 Q*1
Production
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0
74
76
78
80
82
84
86
88
90

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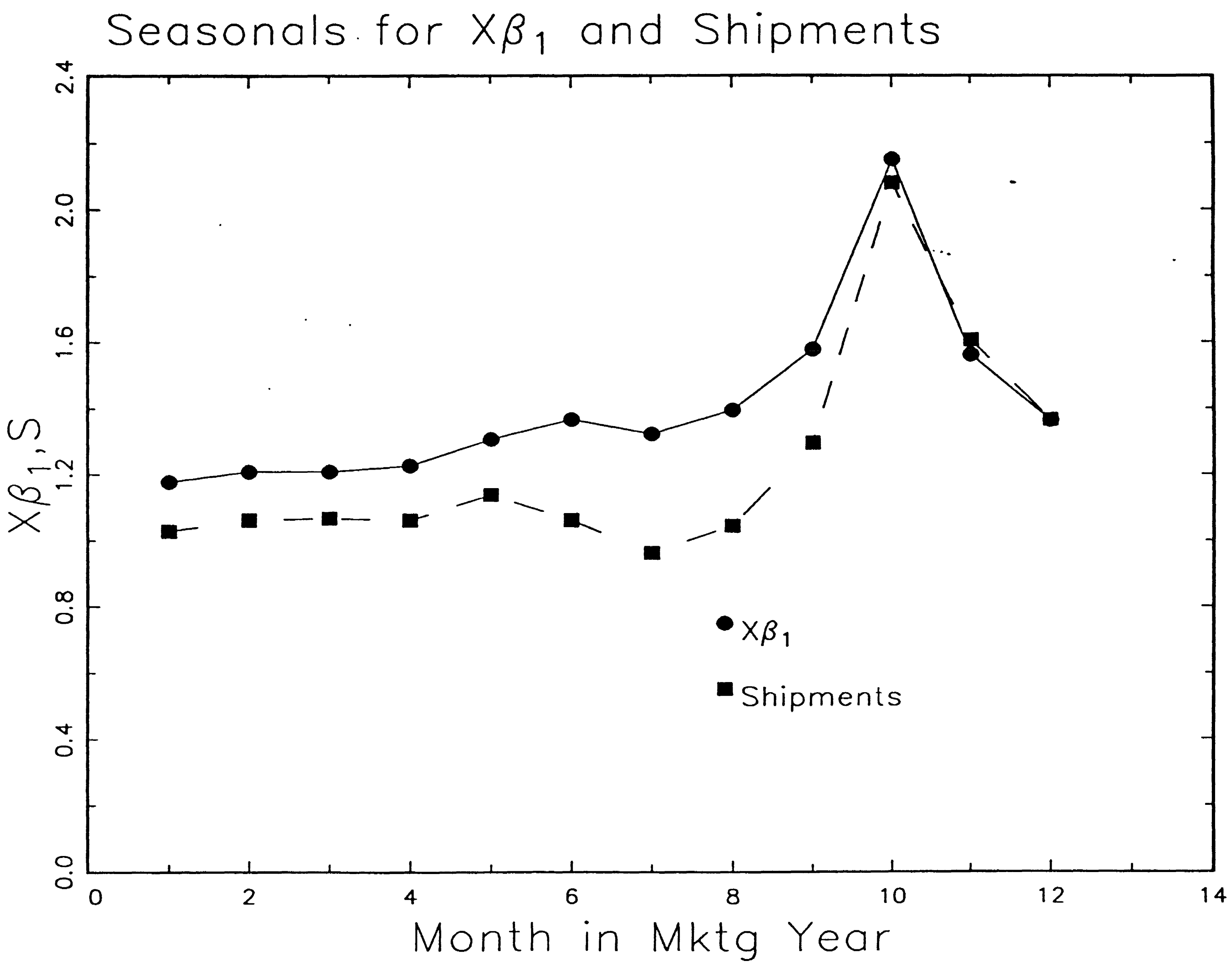

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