Seasonality, Capital Inflexibility, and the Industrialization of Animal Production

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Abstract

Among the prominent recognized features of the industrialization of animal production over the past half century are growth in the stock of inflexible or use-dedicated capital as an input in production and growth in productivity. Less recognized is a trend toward aseasonal production. We record the deseasonalization of animal production in the United States and Europe over the past 70 years. We also suggest that (a) lower seasonality can precede or Granger-cause increased productivity because of increased capital intensity, and (b) productivity improvements can Granger-cause lower seasonality. Process (a) should be more likely earlier in the industrialization process. For U.S. dairy production, our empirical tests find some evidence that process (a) operated early in the twentieth century while process (b) operated in more recent times.

Keywords: capital intensity, causality, dairy, regional production systems.

SEASONALITY, CAPITAL INFLEXIBILITY, AND THE INDUSTRIALIZATION OF ANIMAL PRODUCTION

Agriculture has become more capital intensive in most of the world during the latter part of the twentieth century. This capital deepening has occurred largely in the machinery, irrigation, and buildings categories (Larson et al. 2000). The structural effects have been particularly notable in animal agriculture in the developed world, where the phrases "factory farming" and "industrialized agriculture" correctly depict an animal production process for hogs, chickens, turkeys, and laying eggs that is broadly similar to the prototypical manufacture of widgets. These large farms have increasingly automated production processes, and most workers are employees with routine tasks.

Field crop agriculture on the other hand, though greatly affected by mechanization and other technological innovations, does not yet resemble an industrialized process. Allen and Lueck (2002) argue convincingly that randomness due to weather is primarily responsible because it confounds monitoring in the principal-agent relation, and it requires managerial focus when organizing many mundane production activities. Strengthening control over animal agriculture has involved largely strengthening the control of nature in the production process. Animals have been confined while seasonal aspects of biological behavior have been suppressed through breeding or physiological interventions. Consequences have been the homogenization of the production process and the growing affordability of cheap animal protein in much of the world.

Notwithstanding attention from several academic fields, the process of industrialization at the sector level is not well understood. This is the case in agriculture and in other sectors. Most economic studies on industrialization assume agriculture to be the reference nonindustrial sector, and their insights concerning the details of agriculture are limited. Technology in agriculture is seen to matter because it frees up resources for other uses (Jorgenson 1961; Scitovsky 1954). Kuznets (1968) emphasizes the co-dependency, through spillover effects, between technical change in agriculture and other sectors. This view sees agriculture developing along with other sectors so that all sectors are comparably industrial.

A facet of this viewpoint arises in the induced innovation argument of Hayami and Ruttan (1985). If the price of agricultural labor rises because of increased demand from other sectors, then labor-saving innovations should be induced in response over time.

Studies in economic history have shown evidence that interactions between agricultural seasonality, nonagricultural industrialization, and productivity outside agriculture are likely adverse because industrial plants are most efficient when labor supply is constant (Sokoloff and Dollar 1997; Sokoloff and Tchakerian 1997; Anderson 1931). Our interest is not in the role of agricultural seasonality in external industries but in its role in agriculture itself.

As to what industrialization is, it has many features involving firm behavior, industry structure, the creation of new subsectors, and change in the nature of sector products. Characterizations of industrialization can be found in Meeker 1999, Boehlje 1996, and Drabenstott 1994; in this paper, however, we primarily are interested in firm-level and industry-level behavior regarding technologies used. The technologies should emphasize the control, systemization, and routinization of processes in order to be more assured of product volume and quality at low cost given the larger capital investment necessary for an industrial approach. Regarding the efficiency effects of capital deepening, Chandler (1990, p. 24) has written

> These potential cost advantages could not be fully realized unless a constant flow of materials through the plant or factory was maintained to assure effective capital utilization. If the realized volume of flow fell below capacity, then actual costs per unit rose rapidly. They did so because fixed costs remained much higher and "sunk costs" (the original capital investment) were also much higher than in the more labor-intensive industries.

How industrialization arises is largely a question of structural dynamics because the process is not instantaneous and there is no guarantee it will continue to the point where a sector or economy is recognized as being industrialized. Some inquiries into the path taken suggest the possibility of multiple equilibria (Murphy, Shleifer, and Vishny 1989; Matsuyama 1991; Gans 1997; Chen and Shimomura 1998; Ciccone 2002) so that the economy needs a "big push" to industrialize. As Gans (1998) has pointed out, the existence of multiple equilibria relies on the assumption that firms face two technology choices where one is increasing in returns and the other is a constant-returns reference technology. This “big push” literature leads naturally to policy proposals on engineering an equilibrium, typically a more industrial equilibrium given the increasing returns to scale that are present. Because of its macroeconomic nature, this area of work has little to say about how the particulars of any given industry affect the industrialization process. Our interest is focused on animal agriculture, and we intend to show that sector detail can provide insights on the process.

The formal literature on explaining the agricultural industrialization process is quite sparse. In one sense this is not surprising because the set of events presents somewhat of a conundrum. Agricultural produce is largely commodity in character, while market size is both large and stable. Management of on-farm processes does not require intensive formal training. These technology attributes make the production of food quite like that of cloth or pin manufacture, and so an explanation on the critical distinctions are warranted.

One theory is that agricultural industrialization is demand-led, through increasing demand by consumers and food retailers for information about products and processes (Barkema 1993; Drabenstott 1994; Kinsey 1994). While likely a facet of the subject, as industrialized agriculture can deliver higher quality and more information, demand-side ideas have thus far explained little about the process. The demand-side story is best at explaining changes in control and increasing vertical coordination across much of the food sector. Consumers (or, more likely, their agents) want to peer inside the farm in order to verify quality and caretaking behavior (Hennessy 1996). Processors seek knowledge on product attributes in order to better satisfy consumers. Demand-side arguments do not explain why crop agriculture is not industrial, nor do they explain common features in the technologies that tend to accompany industrialization. Part of the answer must lie in the nature of the process and product.

Allen and Lueck (2002), in extending insights by Becker and Murphy (1992) on the importance of information in coordinating activities, hold that noise and other irregularities in the production process are a reason that crop agriculture has not industrialized. Hennessy, Miranowski, and Babcock (2004) go further to suggest that biotechnology innovations can promote three features of industrialization. These are demand for tight control over the production environment, strong productivity growth, and an increasingly differentiated product. Motivated by Chandler (1990), in this paper we consider two other features of agricultural industrialization: the roles of low variability in throughput and enterprise-dedicated capital in enhancing productivity.[1]

Briefly, our problem is as follows. Animal production has tended to be seasonal largely because of the biology of the animals themselves and the plants with which they are fed. Seasonal production had faced the problem of perishability, together with the unpleasant consequences of storage technologies (e.g., salting). Refrigeration, ease of transportation, and growing international trade have solved most of these problems at a modest cost (Goodwin, Grennes, and Craig 2002). These, by themselves, should promote the extent of production seasonality, and yet we will show that animal production seasonality has declined in recent decades. The resolution of the conundrum lies, we believe, partly in the inflexible nature of capital investments. Unlike labor and the versatile tractor, most other investments in animal agriculture tend to be inflexible in adapting efficiently to seasonality because machines are often dedicated to a particular use.

The intent of this paper is threefold. We complement earlier work by Erdogdu (2002) on the United States by recording the deseasonalization of animal production using time series and statistical trends available for pork, beef, and (mostly) milk production in the Northern Hemisphere during the latter part of the twentieth century. We propose and test a theory on the origins of this deseasonalization and on what it means for the industrialization of agriculture.

Our analysis is structured as follows. We focus on dairying and review some of the most important trends in animal production in the developed world during the last 50 years. Based on monthly production data for dairy, beef, and pork in various countries, we present and discuss seasonality indicators. We then develop a brief causal model of diminishing seasonality. Hypotheses emerge concerning causal relationships between capital intensity and seasonality indices, and we test for evidence on these hypotheses.

The Seasonal Dimension: Dairying

While we see no reason why our theory would not apply to other animal products, we focus attention on dairying for two reasons. First, data on monthly production is readily available and interpretable across several countries. Second, the issue is topical in the dairy sector because traditional systems of more seasonal production remain viable, whereas poultry meats, eggs, and hogs are now produced mainly in nonseasonal systems.

In the traditional U.S. dairy areas of the Upper Midwest, New England, and New York, cows were grazed outdoors during the warmer half of the year. This approach took advantage of cheap in situ grass while surplus grass and other crops made for cheap fodder during the winter when cows were confined. Cows tended to be calved in the spring to match lactation with grass growth. In part because of the perishability of liquid milk and in part because of milk marketing regulations, other regions also produced milk. Dairy farms in some of these regions, especially California, tended to be very different. Scale of production tended to be larger, output was less seasonal, and cows were largely confined in dry lot. During the period 1950-2000, production in the West expanded at the expense of traditional regions and the expanding farms tended to be more industrial.[2]

Table 1 provides an overview of some of the main innovations in U.S. on-farm dairy production over the last century. We categorize them as pro-seasonal (“P” entries), seasonality neutral (“N” entries), or anti-seasonal (“A” entries). The pro-seasonal innovations are provided in the first column. Electric fencing has greatly improved efficiency of in situ grazing, while irrigation technologies have assisted in reducing the weather risk of an outdoor production system. Forage preservation techniques have improved grass utilization efficiency and have helped to maintain the contribution of grass products to the dairy cow

TABLE 1. Seasonal bias in noteworthy dairy production innovations, 1900-2000

Pro-seasonal	Seasonality Neutral	Anti-seasonal
P1. Electric fencing	N1. Genetic Innovation	A1. Artificial insemination
P2. Irrigation technologies	N2. Antibiotics	A2. Housing innovations
P3. Forage preservation innovations	N3. Sanitation technologies	A3. Electricity in milking parlor
P4. Storage innovations for dairy output	N4. Fertilization technologies	A4. Refrigerated bulk tanks
	N5. Tractor	A5. Transfer pipes to bulk tanks
		A6. Mechanized feed handling
		A7. Robotic milking machines
		A8. Downstream processing
		A9. Bulk milk handling/marketing
		A10. Manure handling methods
		A11. Specialization in other outputs
		A12. National transportation and storage innovations for feed

diet. These innovations have altered seasonal costs. Final product storage innovations, entry P4, on the other hand, separate the timing of production from consumption and so allow for more intensive production in low-cost seasons.

Concerning entries in the seasonality-neutral column of Table 1, genetic innovations have increased dramatically the milking cow's productivity. The consequences for seasonality are not readily apparent beyond making two points. The cow's dry period at the end of lactation has declined and this is a very direct way in which increased productivity can cause deseasonalization. There is also reason to believe that high-yielding cows are less robust to weather and disease. They are increasingly bred with a constitution that favors an indoor life, but that may be a consequence of deseasonalization and not a cause. Antibiotics, entry N2, are a substitute for sanitation, entry N3. While the confined cow is easier to monitor and its health regime is easier to maintain, cleanliness can be a problem and communicable disease can also be transmitted more quickly. Fertilization technologies have reduced the costs of concentrated feed, forage, and in situ grazing. In the absence of further information, we place it in the seasonality-neutral column. Finally, the tractor has proved to be just as versatile around the farmyard as in the field, and so the effect on the decision to confine cows is not immediate.

The third column in Table 1 lists what we contend are anti-seasonal innovations. Artificial insemination and housing innovations have diminished the roles of nature in animal production and must be important components of sector industrialization. Entries A3 through A9 are of particular interest to this paper and involve the growing capitalization of animal agriculture. In all cases, the equipment put in place is dedicated and is inelastic with respect to interseasonal substitution.[3] As we will show, this inflexibility should be important in determining the rate of deseasonalization. In entry A10, manure is spread as fertilizer but it is an inconvenient form of plant nutrition. While all dairy production systems produce manure as a result of animal confinement, the problem is most severe for a completely confined production system and so innovations in that area have been most beneficial for nonseasonal production.

U.S. farms have become increasingly specialized in the outputs they produce (see Gardner 2002, p. 61). This likely means there are fewer alternative on-farm uses of dairy farm labor during the low output season. Transportation innovations are also likely to be anti-seasonal, if only because feed and forage input markets have become more integrated and so are less subject to regional effects.

The direct importance of these developments for agricultural productivity has been studied elsewhere in the literature. Of interest to us are their effects on seasonal structure in animal production. In the next section we provide statistical evidence on the nature of change in animal production seasonality over time.

Documenting Seasonal Patterns in Agriculture

Table 2 reports the monthly production data series we have used from the U.S., Canadian (CAN), U.K., and German (DE) sources. The series have been transformed to take account of the different length of the months in a year. That is, monthly production has been divided by the actual number of days to yield average daily production and then normalized to a 30-day month.

Seasonality of production has been measured by two concentration indices. Following Erdogdu (2002), who investigated animal production seasonality at the U.S. state level for hogs, milk, and beef, we use the Herfindahl index ($\mathcal{H}$) and the maximum

TABLE 2. Monthly production data used

Product	Country	Series	Units	Time Covered	Source
Milk	US	Milk production	Million pounds	1930 -2000	USDA-NASS
	DE	Delivery to dairies	Million liters	1951 -2001	*Agrarwirtschaft*
	CAN	Milk production	Thousand liters	1945 -2000	Statistics Canada
	UK	Milk production	Million liters	1936 -2002	Up to Nov. 1994: UK Milk Marketing Board; starting Dec. 1994: Rural Payments Agency
Pork	US[a]	Production	Million pounds	1944 -1981; 1983 -2000	USDA-NASS
	DE[b]	Production	Thousand tons	1951 -1989; 1991 -2000	*Agrarwirtschaft*
	UK	Production	Thousand head	1973 -2000	DEFRA
Beef	US[a]	Production	Million pounds	1944 -1981; 1983 -2000	USDA-NASS
	DE	Slaughter	Thousand head	1951 -2000	*Agrarwirtschaft*
	UK	Slaughter	Thousand head	1973 -2000	DEFRA

[a]U.S. pork and beef monthly production data are missing in 1982, a year in which the NASS service suffered severe budget cuts. To fill in the gap in the time-series data, the calculated $\mathcal{E}$ was filled in using a cubic trend function.
[b]No coherent monthly production data are available for DE pork in the unification year, 1990.

entropy index ($\mathcal{E}$). Denoting month *m* share, $m=1$ for January and $m=12$ for December, in annual production in year *t* as $s_{m,t}$, $\sum_{m=1}^{12} s_{m,t} = 1$, the year *t* value of $\mathcal{H}$ is calculated as $\mathcal{H}_t = \sum_{m=1}^{12} (s_{m,t} \times 100)^2$. Year *t* entropy is $\mathcal{E}_t = -\sum_{m=1}^{12} s_{m,t} \ln(s_{m,t})$. Because $(s_{m,t})^2$ is convex whereas $-s_{m,t} \ln(s_{m,t})$ is concave, an increase in dispersion among monthly shares should be identified by a lower $\mathcal{H}$ and a higher $\mathcal{E}$. In fact, for monthly production shares, $\mathcal{E}$ reaches a maximum of ln(12) = 2.4849 when an equal share of one-twelfth is produced in each month whereas $\mathcal{H}$ has value 833.33 in this case.

For ease of interpretation, we also report the peak-trough ratio of monthly production. In a given year it is calculated as the ratio of production in the month where production is maximum, $s_{\max,t}$, to production in the month where production is minimum, $s_{\min,t}$. The peak-trough ratio is $\mathcal{R}_t = s_{\max,t}/s_{\min,t}$. By definition, $\mathcal{R}$ values are limited to no less than unity, and a value of one would indicate constant production across months in a year. Note also that the peak and trough months may differ across states and years. All analyses to follow have been performed on both $\mathcal{H}$ and $\mathcal{E}$ indices but results are similar and we conserve space by reporting only results using $\mathcal{E}$. Descriptive statistics in the following tables are provided for $\mathcal{R}$ and $\mathcal{E}$, as the former lends itself most readily to intuitive interpretation.

Table 3a reports the calculated indices at the national level. It is obvious that seasonality has declined over time. The most marked decline is in dairy production. Canada, in particular, changed from a strongly seasonal to an essentially nonseasonal system over the period 1950-2000. A similar trend, but to a lesser extent, is observable for pork. For beef, no clear trend toward more or less seasonality is discernable. Table 3b reports the seasonal indices for 14 major U.S. milk producing states, in which monthly data were available from 1950 onwards.[4] The decline over time in seasonal dispersion is quite uniform across states.

An understanding of the regional dimension of Table 3b requires some background on the significance of states in the U.S. dairy industry. Table 4 shows that Wisconsin and California were the two most important milk production states in 2002. These states have had very different production systems, Wisconsin having smaller herds and more

TABLE 3A. Indices of seasonal production, averages per decade

	Peak-Trough Ratio[a]				Entropy Index[b]			
	1930-39	1950-59	1970-79	1990-99	1930-39	1950-59	1970-79	1990-99
Milk								
US	1.5190	1.4940	1.2361	1.1444	2.4746	2.4759	2.4828	2.4842
CAN	–	2.3164	1.6990	1.1208	–	2.4447	2.4699	2.4842
UK	1.4762	1.3996	1.3913	1.2060	2.4765	2.4791	2.4794	2.4833
DE	–	1.6512	1.4519	1.2182	–	2.4708	2.4772	2.4829
Pork								
US	–	1.6294	1.3919	1.2668	–	2.4728	2.4804	2.4824
UK	–	–	1.3980	1.4198	–	–	2.4788	2.4789
DE	–	1.3007	1.1616	1.2194	–	2.4817	2.4839	2.4833
Beef								
US	–	1.2855	1.2207	1.2096	–	2.4823	2.4833	2.4832
UK	–	–	1.5736	1.8329	–	–	2.4750	2.4708
DE	–	1.4325	1.3455	1.4542	–	2.4784	2.4805	2.4785

[a]A decline in the index represents a decline in the seasonality of production.
[b]A rise in the index represents a decline in the seasonality of production.

TABLE 3B. Indices of seasonal production, averages per decade

	Peak-Trough Ratio[a]			Entropy Index[b]		
State	1950-59	1970-79	1990-99	1950-59	1970-79	1990-99
CA	1.262	1.159	1.087	2.4818	2.4838	2.4846
ID	1.498	1.259	1.158	2.4754	2.4822	2.4836
IL	1.468	1.205	1.146	2.4773	2.4831	2.4837
IN	1.518	1.174	1.110	2.4755	2.4837	2.4843
KY	1.742	1.445	1.184	2.4647	2.4779	2.4834
MI	1.435	1.107	1.084	2.4786	2.4844	2.4846
MN	1.927	1.465	1.153	2.4613	2.4750	2.4835
NY	1.505	1.227	1.105	2.4751	2.4825	2.4844
OH	1.413	1.191	1.122	2.4782	2.4835	2.4841
PN	1.367	1.157	1.101	2.4802	2.4839	2.4844
TX	1.320	1.145	1.302	2.4804	2.4839	2.4808
VA	1.386	1.150	1.149	2.4778	2.4838	2.4840
WA	1.498	1.184	1.083	2.4761	2.4835	2.4846
WI	1.695	1.322	1.134	2.4697	2.4809	2.4841

[a] A decline in the index represents a decline in the seasonality of production.
[b] A rise in the index represents a decline in the seasonality of production.

pronounced production seasonality.[5] Beginning in 1950, California quadrupled production share to move from fourth to first in production. Wisconsin's production share grew from 12.7 percent to beyond 17 percent in 1980 before declining to 13 percent by 2002. The less significant midwestern states have lost production uniformly since 1950 with the exception of Minnesota and Wisconsin; Minnesota's relative decline commenced around 1970. The significant eastern states of New York and Pennsylvania saw a growth in national share before a relative decline set in over the twenty years commencing about

TABLE 4. Dairy production shares by U.S. state and by decade, 1950-2002

State	1950	1960	1970	1980	1990	2002
CA	5.1	6.5↑[a]	8.1↑	10.6↑	14.2↑	20.5↑
ID	1.0	1.3↑	1.3↓	1.5↑	2.0↑	4.8↑
IL	4.5	3.4↓	2.4↓	2.0↓	1.7↓	1.2↓
IN	3.2	2.6↓	2.0↓	1.7↓	1.5↓	1.5
KY	2.1	2.1	2.1	1.7↓	1.5↓	1.0↓
MI	4.6	4.2↓	3.9↓	3.9	3.5↓	3.5
MN	6.9	8.4↑	8.2↓	7.4↓	6.8↓	5.0↓
NY	7.6	8.4↑	8.8↑	8.5↓	7.5↓	7.2↓
OH	4.5	4.3↓	3.8↓	3.4↓	3.2↓	2.6↓
PA	4.8	5.6↑	6.1↑	6.6↑	6.8↑	6.3↓
TX	3.0	2.4↓	2.6↑	2.8↑	3.7↑	3.1↓
VA	1.7	1.5↓	1.5	1.5	1.4↓	1.1↓
WA	1.5	1.5	1.8↑	2.3↑	3.0↑	3.3↑
WI	12.7	14.3↑	15.8↑	17.4↑	16.4↓	13.0↓
$\mathcal{H}$, U.S. level	407	501	566	651	691	786

[a] The arrows indicate the direction of change in shares since the previous decade.

1980. Southern states, small producers to begin with, have largely contracted while the parched western and mountain states have expanded.

To understand the dynamics behind the decline in seasonality as reported in Tables 3a and 3b, we test the hypothesis that $\mathcal{E}$ is converging to a nonseasonal system. If deseasonalization follows a geometric convergence process, then it can be modeled as $\bar{\mathcal{E}} - \mathcal{E}_t = a_1(\bar{\mathcal{E}} - \mathcal{E}_{t-1})$, $\bar{\mathcal{E}} = \ln(12)$. This is equivalent to an autoregressive order 1 (AR1) process:

$$\mathcal{E}_t = a_0 + a_1\mathcal{E}_{t-1}, \tag{1}$$

with the restriction on the constant that $a_0 = (1 - a_1)\bar{\mathcal{E}}$. In this process, a_1 is the convergence rate: the higher its value, the faster $\mathcal{E}$ converges to $\bar{\mathcal{E}}$.

The results are given in Tables 5 and 6. These tables also provide test statistics for the hypothesis H_0: $a_0 = (1 - a_1)\bar{\mathcal{E}}$, that is, whether constant geometric convergence to the nonseasonal system is an appropriate model. Looking at the results for the different countries in Table 5, the hypothesis of geometric convergence is rejected in all cases except for milk in Canada and the United States. The convergence rates for milk vary between 0.842 in the United Kingdom and 0.975 in Canada. Convergence rates are considerably lower, but still significant, for pork where they vary between 0.176 in

TABLE 5. Trends in deseasonalization—animal production in selected countries

	a_0, (t-value)[a]	a_1, (t-value)	R^2	Durbin-Watson	p-value, $a_0 = (1-a_1)\overline{\varepsilon}$
Milk					
UK	0.391**	0.842***	0.703	2.304	0.021
	(0.170)	(0.068)			
DE	0.207*	0.917***	0.879	2.841	0.089
	(0.122)	(0.049)			
CAN	0.062	0.975***	0.939	2.631	0.151
	(0.043)	(0.030			
US	0.076	0.969***	0.983	2.608	0.306
	(0.075)	(0.030)			
Pork					
UK	1.234**	0.502**	0.212	2.044	0.010
	(0.479)	(0.193)			
DE	2.046***	0.176**	0.098	1.708	0.000
	(0.193)	(0.078)			
US	0.809***	0.673***	0.456	2.222	0.001
	(0.250)	(0.101)			
Beef					
UK	1.599***	0.354*	0.128	1.996	0.000
	(0.457)	(0.185)			
DE	2.469***	0.004	0.001	1.965	0.000
	(0.360)	(0.145)			
US	2.198***	0.114	0.013	2.002	0.000
	(0.339)	(0.137)			

[a] *, **, and *** identify significance at the 10%, 5%, and 1% levels, respectively.

Germany and 0.672 in the United States. They are insignificantly different from zero for beef in Germany and in the United States. Table 6 reports similar results for the 14 U.S. dairy states. Convergence to a completely aseasonal system is rejected at the 5 percent significance level except for Minnesota. Nonetheless, significant convergence rates are observed, varying between 0.775 and 0.929. Overall convergence rates in these states are lower than for the United States as a whole. For both tables, the estimated convergence parameters are sufficiently large to suggest the existence of a unit root and we will formally test for unit roots at a later juncture.

As will be explained shortly, changes in animal productivity are important in our inquiry into the nature of deseasonalization. Here we have reliable indicators only for milk in the United States, Canada, Germany, and the United Kingdom and for pork in the United States. Milk yield per cow in liters or gallons is used as the productivity indicator in dairying. Measures of hog productivity in the growing phase are more difficult to obtain and we use the breeding phase indicator of average litter size of farrowing sows.

TABLE 6. Trends in deseasonalization–dairy production in selected U.S. states

	a_0, (t-value)[a]	a_1, (t-value)	R^2	Durbin-Watson	p-value, $a_0 = (1 - a_1)\overline{\varepsilon}$
CA	0.470*** (0.119)	0.811*** (0.048)	0.848	3.039	0.000
ID	0.362*** (0.108)	0.854*** (0.043)	0.886	2.361	0.001
IL	0.351** (0.141)	0.859*** (0.057)	0.820	2.423	0.013
IN	0.229*** (0.084)	0.908*** (0.034)	0.934	2.379	0.007
KY	0.322 (0.116)	0.870*** (0.047)	0.874	2.749	0.005
MI	0.228*** (0.063)	0.908*** (0.026)	0.962	2.087	0.000
MN	0.176 (0.112)	0.929*** (0.045)	0.894	2.799	0.116
NY	0.247* (0.088)	0.900*** (0.035)	0.928	2.741	0.005
OH	0.458*** (0.135)	0.815*** (0.054)	0.818	2.700	0.001
PA	0.272** (0.131)	0.890*** (0.053)	0.851	2.843	0.037
TX	0.558*** (0.172)	0.775*** (0.069)	0.714	2.086	0.001
VA	0.302*** (0.098)	0.878*** (0.039)	0.908	2.819	0.002
WA	0.266*** (0.060)	0.893*** (0.024)	0.964	2.659	0.000
WI	0.267*** (0.098)	0.892*** (0.039)	0.911	2.378	0.006

[a] *, **, and *** identify significance at the 10%, 5%, and 1% levels, respectively.

Theoretical Motivation

Our intention is to explore interactions between productivity and seasonality. Equipped with these indicators and considering the dynamics of the seasonal structure of the dairy industry in the United States, Table 7 shows correlations between seasonality, productivity, and production shares for the 14 U.S. dairy states listed in Table 6. These correlations were calculated based on 1950 data for the fourteen states, and again on 2000 data. In 1950, when the high seasonality systems of the upper Midwest had large shares in U.S. total production, a negative correlation existed between production shares (the Shares row in Table 7) and aseasonality. This negative relationship turned into a positive one in 2000 because by then the aseasonal western state production systems had large shares in U.S. production.

TABLE 7. Correlation between production shares, seasonality, and productivity in 14 dairy states in 1950 and 2000

	$\mathcal{E}$		$\mathcal{P}$	
	1950	**2000**	**1950**	**2000**
Shares	-0.231	0.256	0.459	0.402
$\mathcal{E}$			0.194	0.358

The relation between productivity and production shares is, as expected, positive in both periods but it declined slightly from 0.459 in 1950 to 0.402 in 2000. This decline indicates that other factors are important. We look next at what motivated the closeness in relation between aseasonality and productivity (shown in the lower right part of the table). The relationship has always been positive for the data periods covered but has become much stronger over the last 50 years, increasing from 0.194 in 1950 to 0.358 in 2000.

Model

A representative farm produces animal output in two seasons; season A is high cost while season B is low cost. Outputs q_A and q_B are produced in seasons A and B, respectively. There are four types of costs. There are seasonal unit costs labeled as c_A and c_B, respectively, where $c_A > c_B$ and these costs amount to $c_A q_A + c_B q_B$ per annum. There is a season-dependent convex cost function $C(q_A, q_B)$ that captures decreasing returns to scale. This cost function is also symmetric, $C(q_A = \hat{q}_A, q_B = \hat{q}_B) \equiv C(q_A = \hat{q}_B, q_B = \hat{q}_A)$. There are season-invariant unit costs labeled as $\bar{c}$, and this unit cost parameter will change as a result of technical innovations. These costs amount to $\bar{c} q_A + \bar{c} q_B$ per annum. Finally, there are per annum peak-load unit capital costs amounting to $F \max[q_A, q_B]$. As with $\bar{c}$, parameter F can change as a result of technical innovations.

The price-taking firm obtains season-invariant market price P per unit sold where the assumption has been made that product is storable at zero cost. The firm's annual profit is then

$$\pi = (P - \bar{c}) \times (q_A + q_B) - c_A q_A - c_B q_B - C(q_A, q_B) - F \max[q_A, q_B]. \tag{2}$$

Denote the optimal output choices as q_A^* and q_B^*. The symmetry of $C(q_A, q_B)$ allows us to readily conclude that optimum outputs satisfy $(c_A - c_B)(q_A^* - q_B^*) \le 0$ and so that $q_A^* \le q_B^*$. We characterize capital-intensive innovations as follows. They increase unit peak load capital cost F while also decreasing unit season-invariant cost $\overline{c}$. The sorts of innovations considered here include entries A2 through A9 in Table 1. The innovation will be adopted if the trade-off between costs is sufficiently favorable. Using the envelope theorem on equation (2), profit-increasing innovations are ones that satisfy $\partial\overline{c} / \partial F \le -q_B^* / (q_A^* + q_B^*)$.

Characterize the distribution of trade-offs on available innovations $x = \partial\overline{c} / \partial F$ as discrete measure $\mu(X): (-\infty, 0] \to [0,1]$ where X is a set of the form $(-\infty, x], x \in -\overline{\mathbb{R}}_+$, $\overline{\mathbb{R}}_+$ the nonnegative reals. The normalization to $[0,1]$ is a convenience, and the most profitable among available innovations to adopt are those with low x values. They most reduce costs $\overline{c}q_A + \overline{c}q_B$ relative to the cost increase arising from the required increase in F. Firms adopt innovations with trade-offs up to the critical trade-off ratio $-q_B^* / (q_A^* + q_B^*)$ so that the set of adopted capital-intensive innovations among those available has the measure $\mu((-\infty, -q_B^* / (q_A^* + q_B^*)])$. This measure is largest, at $\mu((-\infty, 0.5])$, when the seasonality peak-trough ratio q_B^* / q_A^* is smallest.

PROPOSITION 1. *As seasonality decreases, that is, the peak-trough ratio decreases, the rate of adoption of capital-intensive innovations increases.*

The proposition can be interpreted in two ways. Suppose some multi-use innovation with a barnyard application (e.g., electricity or vacuum tubes) is commercialized. If it so happens that the innovation has an anti-seasonal bias, so that seasonality decreases, then we should see a pick-up in the adoption of capital-intense innovations that are already available to dairy producers. Alternatively, from Table 3b we could take a regional perspective and conclude that seasonal production systems in Wisconsin and Minnesota should be less capital intensive than the California system.

This proposition would, by itself, suggest that deseasonalization should precede productivity growth when productivity growth is primarily in the form of season-inflexible capital. However, the peak-load capital cost has another effect. Suppose that $C(q_A, q_B)$ takes the homothetic constant-elasticity-of-substitution form $C(q_A, q_B) = \hat{C}[(q_A^\rho + q_B^\rho)^{1/\rho}], \rho > 1$. The optimality condition for an interior solution with $q_B^* > q_A^*$ is

$$\frac{q_B^*}{q_A^*} = \left(\frac{P - \bar{c} - c_B - F}{P - \bar{c} - c_A} \right)^{1/(\rho-1)}, \tag{3}$$

and, given $c_A > c_B$, consistency requires that $c_A > c_B + F$. If, instead, $c_A \le c_B + F$, then the farm would not produce more in season B than in season A because the marginal cost of season B production would (weakly) exceed that of season A production. Nor would the farm produce more in season A because $c_B < c_A + F$. So $q_A^* = q_B^*$ when $c_A \le c_B + F$.

Differentiate (3) with respect to F, taking into account the associated change in $\bar{c}$, $d\bar{c}/dF \;\; < 0$, to obtain

$$\frac{d(q_B^*/q_A^*)}{dF}\Big|_{\substack{\bar{c} \\ changes}} = \frac{1}{\rho - 1} \left(\frac{P - \bar{c} - c_B - F}{P - \bar{c} - c_A} \right)^{(2-\rho)/(\rho-1)} \frac{c_A + \bar{c} - P + (c_A - c_B - F) d\bar{c}/dF}{(P - \bar{c} - c_A)^2}. \tag{4}$$

The number is negative when $c_A > c_B + F$, and so more capital intensity decreases the peak-trough ratio. When $c_A \le c_B + F$, then $q_A^* = q_B^*$ remains valid under the higher F value.

PROPOSITION 2. *Let* $C(q_A, q_B) = \hat{C}[(q_A^\rho + q_B^\rho)^{1/\rho}], \rho > 1$, *with* $c_A > c_B$. *Let capital intensity increase, that is,* F *increases and* $\bar{c}$ *decreases, by a sufficient amount such that the new cost structure is adopted. Then production seasonality, as represented by peak-trough ratio* q_B^* / q_A^*, *decreases if greater than unity and does not change if equal to unity.*

This proposition would suggest that productivity growth induced by capital intensity should precede deseasonalization. It is not a contradiction of Proposition 1 because causality between series can be two-way, each reinforcing the other. Note though that it is only when there is a base of capital-intensive innovations, that is, $F > 0$, that the model suggests productivity growth should precede deseasonalization. When F is low, one should expect to see deseasonalization before capital-intensity-induced productivity growth in order to establish a capital base in the production system.

CLAIM 3. *For farms with low capital intensity, deseasonalization should precede capital-intensity-induced productivity growth. For farms with high capital intensity, capital-intensity-induced productivity growth should precede deseasonalization.*

Empirical Relationships between Productivity and Seasonality

We have just identified conditions under which an increase in productivity can induce a reduction in seasonality and under which the reversed causal relationship can pertain. From this perspective, $\text{Cov}(\mathcal{E}, \mathcal{P})$ in Table 7 warrants further scrutiny. We test for causal pathways in Northern Hemisphere milk production data.

Since the work of Yule (1926), the danger of spurious regressions in testing for causality among time series has been recognized. Evaluating the relationship of economic time-series data often results in highly autocorrelated residuals and may bias conventional hypothesis tests (Granger and Newbold 1974). To circumvent this problem, it has become common practice to first test for cointegration among the series. If series are known to be integrated of order one, denoted by I(1), but not cointegrated, the practice is to estimate a vector autoregressive regression (VAR) model on differences. Alternatively, if the series are known to be cointegrated then causality can be determined using an error-correction model. Since the procedure will depend on the result of the pretest, we adopt a procedure proposed by Dolado and Lütkepohl (1996). This procedure is robust to the degree of cointegration and so avoids possible problems with pretesting. Nonetheless, we first test for unit roots and cointegration.

Stationarity Tests

Using the Dickey-Fuller procedure we test for stationarity in the $\mathcal{E}$ and $\mathcal{P}$ indices. The Dickey-Fuller test is restrictive in that it assumes statistically independent error terms of constant variance. Phillips and Perron (1988) have developed a generalization of the Dickey-Fuller procedure that relaxes the assumption on the error terms, but their test is problematic when the true model contains a negative moving average. Because the true model is never known, Enders (1995) suggests performing both tests. We do so and the results for $\mathcal{P}$ and $\mathcal{E}$ are reported in Table 8, both at the country and U.S. state levels. The table shows the test statistics, followed by the p-value in parentheses and the number of lags used in brackets. We cannot reject a unit root in most cases. For German milk, the null of a unit root in $\mathcal{E}$ is rejected according to both augmented Dickey-Fuller and Phillips-Perron tests. For U.S. pork, it is rejected under the augmented Dickey-Fuller test. For all states, evidence is inconclusive on the existence of a unit root in $\mathcal{E}$. While it is rejected according to the augmented Dickey-Fuller (Phillips-Perron) test in California, Indiana, Michigan, New York, Ohio, Washington (Idaho, Minnesota), it is then accepted in the other test. The existence of a unit root in the productivity series is only rejected at the 10 percent level in Kentucky under both tests, in California and Texas according to the Phillips-Perron test, and in Washington according to the augmented Dickey-Fuller test.

Cointegration

Assuming that unit roots do exist, we proceed with tests of cointegration. We use the Johansen maximum-likelihood method (Johansen 1988; Johansen and Juselius 1990) that is based on a full system approach. We test for cointegration based on the trace statistics of the integrating vectors. In addition, the Engle-Granger method is used. The latter is a single-equation method and it tests for the unit root in the residual of these cointegrating regressions.

The results are reported in Table 9. The results obtained using the Engle-Granger method suggest that the productivity and seasonality series are cointegrated in Pennsylvania and Washington. The outcome of the Johansen method provides even more evidence of the need to accommodate possible cointegration. The trace test rejects the null hypothesis of no cointegration (the rank of the characteristic roots equal to zero) for milk in the United Kingdom, California, Ohio, Pennsylvania, and Washington. As explained below, the way in which causality tests are conducted depends on the presence of integrated and/or cointegrated series.

TABLE 8. Unit-root tests for entropy and productivity in milk production

	$\mathcal{E}$		$\mathcal{P}$	
	Augmented Dickey-Fuller	**Phillips-Perron**	**Augmented Dickey-Fuller**	**Phillips-Perron**
US-Milk	-2.847 (0.180) [10]	-9.722 (0.455) [10]	-1.484 (0.835) [2]	-2.281 (0.962) [2]
CAN-Milk	0.138 (0.995) [3]	-4.584 (0.850) [3]	-0.332 (0.989) [2]	-0.926 (0.989) [2]
UK-Milk	-2.141 (0.523) [2]	-17.964 (0.106) [2]	-1.605 (0.790) [2]	-14.281 (0.212] [2]
DE-Milk	-3.669 (0.024) [2]	-31.356 (0.007) [2]	-1.300 (0.888) [5]	-6.298 (0.722) [5]
US-Pork	-4.745 (0.001) [10]	-37.025 (0.002) [10]	0.049 (0.995) [2]	-1.909 (0.972) [2]
U.S. States-Milk				
CA	-3.989 (0.009) [2]	-13.013 (0.266) [2]	-2.897 (0.163) [2]	-28.111 (0.013) [2]
ID	-2.681 (0.244) [10]	-19.550 (0.077) [10]	-0.664 (0.975) [4]	-2.067 (0.968) [4]
IL	-0.876 (0.959) [4]	-9.474 (0.473) [4]	-1.041 (0.938) [2]	-3.328 (0.922) [4]
IN	-4.830 (0.0004) [6]	-3.061 (0.934) [6]	-1.862 (0.674) [3]	-7.301 (0.640) [3]
KY	-0.756 (0.969) [3]	-16.303 (0.145) [3]	-3.688 (0.023) [3]	-24.012 (0.031) [3]
MI	-3.534 (0.036) [2]	-3.661 (0.906) [2]	-1.554 (0.810) [2]	-7.625 (0.614) [2]
MN	-1.002 (0.944) [4]	-24.935 (0.026) [4]	-1.298 (0.888) [2]	-5.144 (0.811) [2]
NY	-4.190 (0.005) [9]	-6.943 (0.669) [9]	-1.435 (0.850) [2]	-5.915 (0.752) [2]
OH	-5.153 (0.0001) [2]	-8.773 (0.524) [2]	-1.668 (0.765) [9]	-16.116 (0.151) [9]
PA	-0.767 (0.968) [4]	-12.154 (0.308) [4]	-1.602 (0.791) [2]	-5.574 (0.779) [2]
TX	-0.894 (0.957) [10]	-8.917 (0.513) [10]	-1.994 (0.605) [3]	-20.738 (0.061) [3]
VA	-1.429 (0.852) [10]	-5.396 (0.792) [10]	-1.634 (0.524) [2]	-8.774 (0.524) [2]
WA	-4.731 (0.001) [10]	-5.918 (0.752) [10]	-3.252 (0.075) 10]	-9.585 (0.465) [2]
WI	-2.418 (0.370) [6]	-8.054 (0.579) [6]	-2.307 (0.430) [2]	-10.942 (0.376) [2]

TABLE 9. Johansen and Engle-Granger test

	Johansen[a] Trace Statistic	Dep. Var.	Engel–Granger[b] (H_0: no cointegration) t-test	p-value
US-$\mathcal{E}$-Milk	12.839 (0.244) [2]	US-Milk-$\mathcal{E}$	-2.795	0.361 [10]
		US-Milk-$\mathcal{P}$	-0.493	0.994 [7]
CAN-$\mathcal{E}$	12.705 (0.250) [1]	CAN-Milk-$\mathcal{E}$	-2.043	0.753 [2]
		CAN-Milk-$\mathcal{P}$	-2.111	0.723 [2]
UK-$\mathcal{E}$	21.879 (0.015) [1]	UK-Milk-$\mathcal{E}$	-3.079	0.231 [4]
		UK-Milk-$\mathcal{P}$	-2.827	0.345 [10]
DE-$\mathcal{E}$	15.619 (0.114) [2]	DE-Milk-$\mathcal{E}$	-3.042	0.246 [4]
		DE-Milk-$\mathcal{P}$	-0.738	0.989 [2]
US-$\mathcal{E}$-Pork	13.258 (0.218) [11]	US-Pork-$\mathcal{E}$	-1.560	0.909 [10]
		US-Pork-$\mathcal{P}$	-1.674	0.882 [7]
U.S. States (Milk Only)				
CA-$\mathcal{E}$	35.148 (0.0004) [1]	CA-$\mathcal{E}$	-2.935	0.293 [2]
		CA-$\mathcal{P}$	-3.060	0.238 [2]
ID-$\mathcal{E}$	12.269 (0.284) [2]	ID-$\mathcal{E}$	-2.946	0.288 [2]
		ID-$\mathcal{P}$	-2.084	0.735 [2]
IL-$\mathcal{E}$	15.079 (0.133) [1]	IL-$\mathcal{E}$	-3.227	0.176 [2]
		IL-$\mathcal{P}$	-1.879	0.818 [2]
IN-$\mathcal{E}$	11.151 (0.372) [2]	IN-$\mathcal{E}$	-2.257	0.652 [3]
		IN-$\mathcal{P}$	-2.072	0.741 [3]
KY-$\mathcal{E}$	14.030 (0.177) [6]	KY-$\mathcal{E}$	-1.110	0.970 [3]
		KY-$\mathcal{P}$	-3.450	0.111 [3]
MI-$\mathcal{E}$	15.494 (0.118) [2]	MI-$\mathcal{E}$	-2.347	0.604 [2]
		MI-$\mathcal{P}$	-2.193	0.683 [2]
MN-$\mathcal{E}$	8.450 (0.608) [3]	MN-$\mathcal{E}$	-2.493	0.524 [4]
		MN-$\mathcal{P}$	-2.270	0.645 [2]
NY-$\mathcal{E}$	14.433 (0.159) [1]	NY-$\mathcal{E}$	-1.798	0.846 [2]
		NY-$\mathcal{P}$	-1.863	0.824 [2]
OH-$\mathcal{E}$	22.494 (0.013) [9]	OH-$\mathcal{E}$	-1.743	0.863 [3]
		OH-$\mathcal{P}$	-1.745	0.862 [9]
PA-$\mathcal{E}$	21.920 (0.015) [3]	PA-$\mathcal{E}$	-3.536	0.091 [2]
		PA-$\mathcal{P}$	-3.628	0.074 [2]
TX-$\mathcal{E}$	9.684 (0.500) [11]	TX-$\mathcal{E}$	-1.139	0.968 [10]
		TX-$\mathcal{P}$	-2.559	0.487 [2]
VA-$\mathcal{E}$	13.066 (0.230) [2]	VA-$\mathcal{E}$	-1.423	0.960 [10]
		VA-$\mathcal{P}$	-1.986	0.777 [2]
WA-$\mathcal{E}$	24.755 (0.007) [3]	WA-$\mathcal{E}$	-2.325	0.616 [2]
		WA-$\mathcal{P}$	-3.496	0.100 [2]
WI-$\mathcal{E}$	23.208 (0.011) [1]	WI-$\mathcal{E}$	-2.866	0.325 [2]
		WI-$\mathcal{P}$	-3.094	0.225 [2]

[a] Trace statistic stands for the Johansen trace statistic using a finite-sample correction (Hall and Cummins 1999). The null hypothesis of p=0 indicates tests for no cointegration against the alternative of one or more cointgrating vectors (p>0). The p-value is reported in parentheses. The optimal lag length was chosen using the Akaike-Information Criterion and is indicated in brackets.

[b] In the Engle-Granger method, a large p-value shows evidence against cointegration. The optimal lag length was chosen using the Akaike-Information Criterion and is indicated in brackets.

Causality

Standard Granger-causality tests have nonstandard asymptotic properties if the variables of a VAR are integrated or cointegrated. This complicates the tests for causality because one has to resort to simulations to determine the critical value in a causality test. The standard approach in this case has been to estimate a VAR in differences if the variables are known to be I(1) but not cointegrated, or to estimate an error-correction model if the variables are known to be cointegrated (Mosconi and Giannini 1992). An alternative is to employ an approach developed by Dolado and Lütkepohl (1996) and employed in Tsionas 2003, for example. Dolado and Lütkepohl have shown that if variables are $I(d)$ and the true data-generating process is $\mathrm{VAR}(p)$, then fitting $\mathrm{VAR}(p+d)$ results in the usual asymptotics for Wald tests. This works because over-parameterization of the VAR process avoids singularity in the test statistic. As Tsionas explains, in order to test for causality, fit a $\mathrm{VAR}(p+d)$ in levels and then apply a standard F-test involving the coefficients of lags 1 to *p*.

The $\mathrm{VAR}(p+d)$ model for the commodity in state *j* is

$$\begin{pmatrix} \mathcal{E}_{j,t} \\ \mathcal{P}_{j,t} \end{pmatrix} = \begin{pmatrix} a_0 \\ b_0 \end{pmatrix} + \begin{pmatrix} a_{11}^j & \cdots & a_{1p}^j & a_{1p+1}^j & \cdots & a_{1p+d}^j & b_{11}^j & \cdots & b_{1p}^j & b_{1p+1}^j & \cdots & b_{1p+d}^j \\ a_{21}^j & \cdots & a_{2p}^j & a_{2p+1}^j & \cdots & a_{2p+d}^j & b_{21}^j & \cdots & b_{2p}^j & b_{2p+1}^j & \cdots & b_{2p+d}^j \end{pmatrix} \begin{pmatrix} \mathcal{E}_{j,t-1} \\ \vdots \\ \mathcal{E}_{j,t-p} \\ \mathcal{E}_{j,t-p-1} \\ \vdots \\ \mathcal{E}_{j,t-p-d} \\ \mathcal{P}_{j,t-1} \\ \vdots \\ \mathcal{P}_{j,t-p} \\ \mathcal{P}_{j,t-p-1} \\ \vdots \\ \mathcal{P}_{j,t-p-d} \end{pmatrix} \quad (5)$$

where $(\mathcal{P}_{j,t}, \mathcal{P}_{j,t-1}, \ldots, \mathcal{P}_{j,t-p-d})$ is the vector of productivities for the commodity in region *j* at time *t*. The $a_{..}^j$ and $b_{..}^j$ parameters pertain to the seasonality and productivity indicators, respectively. The true VAR model is thought to go up to lag *p*, and the remaining *d* lags are included to make estimates amenable to Wald tests (Dolado and Lütkepohl

1996). According to Dolado and Lütkepohl, the following causality tests are performed. For deseasonalization to cause productivity gains, $H_0 : a_{21} = a_{22} = ... = a_{2p} = 0$ should be rejected. For productivity gains to precede deseasonalization, $H_0 : b_{11} = b_{12} = ... = b_{1p} = 0$ should be rejected.

As to the formal test of equation (5), it is based on the assumption that the structural relationship and the parameters, such as mean, variance, and trend, do not change over time. When dealing with long time series this assumption is likely unrealistic, and structural breaks in at least one parameter are likely. A classical testing procedure for structural change is based on Chow's (1960) test, which applies for a known break date. The sample is split into two subsamples, estimates are made of the parameters for each subsample, and an F-test is applied on the equality of parameters. The limit of this test is that the break date must be known a priori (Hansen 2001).

Alternatively, the timing of the structural change can be estimated. As we have no a priori knowledge of any break in the relationship, we would like the data to tell us if and when a break occurred. Bai (1997) proposes a least squares estimation of a change point in multiple regressions. The analysis is extended in Bai and Perron 1998 and in Bai, Lumsdaine, and Stock 1998 in two ways. Bai and Perron develop the procedure to estimate multiple structural changes occurring at unknown dates. Bai, Lumsdaine, and Stock construct confidence intervals for the date of a single break in multivariate time series, including I(0), I(1), and deterministically trending regressors. In this latter test, the width of the asymptotic confidence interval does not decrease with sample size but is inversely related to the number of series that have a common break date. A similar approach is developed in Murray and Papell 2000. The approach of estimating a single break point on multivariate time series proposed in Bai, Lumsdaine, and Stock is extended to multiple break points in Bai 2000.

Following Bai (2000), we use a quasi-likelihood ratio procedure to estimate the change date. For the VAR(p+d) model in (5), the method compares the quasi-likelihood ratio estimated over the entire sample based on a single parameter vector with the pair of quasi-likelihood ratios obtained by estimating over the period before and the period after the break. If the log quasi-likelihood of the whole sample exceeds the sum across the pair of time periods, then we assert that a break is not present and we choose the whole-sample estimates. Otherwise, we assert a break at the identified point. Since in the case with a break the subsample estimates are completely independent, all parameters including the variance of the error term may differ. With this approach to estimating the VAR(p+d) model we apply the procedure of Dolado and Lütkepohl to test for causality.

Results for sovereign countries and U.S. states are presented in Table 10. The first column indicates the country/state and commodity. For each pair, but with three exceptions, tests are performed on two periods. Two exceptions are Texas milk and Washington milk, for which no date break was detected. The third exception is U.S. milk, where we detect a second break. The break year is indicated in the third column and is the year in which the earlier parameter regime ends. Note that the beginning year of the first regime and the ending year of the final regime depend on data availability as indicated in Table 2.[6] The fourth column reports on the optimal number of lags, p, to be included in the VAR analysis based on the Schwartz-Bayesian information criterion.

The results of the causality tests are reported in columns 5-6 and 7-8. Columns 5 and 6 report the test statistic and respective p-value for the hypothesis that productivity growth causes, or precedes, a decline in seasonality. Columns 7 and 8 do the same for the reverse hypothesis that a decline in seasonality precedes productivity growth. Note that the hypotheses are not mutually exclusive. It could happen that both hypotheses are accepted (two-way causality), or that neither hypothesis is accepted (no causality). To help the reader in interpreting the results, we include a final column indicating any detected causal relationship.

We turn first to the results on sovereign countries. For dairy, only milk production in the United States gives a significant result in the causality test. There are two breaks, in 1957 and 1979.[7] The test shows that for the period prior to 1957, deseasonalization (growth in ε) preceded productivity growth. For each other country and commodity, there is one break and it occurs early in the last quarter of the century. For instance, with Canadian milk, U.K. milk, and U.S. pork the break occurs in the early 1980s while it occurs at about 1975 for milk in Germany.

TABLE 10. Dolado and Lütkepohl causality test for aseasonality and productivity

State/ Commodity	Causality	Break Year	Number of lags p[a]	$\mathcal{P} \to \mathcal{E}$ χ^2-test	$\mathcal{P} \to \mathcal{E}$ p-value	$\mathcal{E} \to \mathcal{P}$ χ^2-test	$\mathcal{E} \to \mathcal{P}$ p-value	Conclusion
Countries								
US-Milk	1st period	1957, 1979	1	0.228	0.633	2.789	0.095	$\mathcal{E} \to \mathcal{P}$
	2nd period			0.401	0.527	0.064	0.801	-
	3rd period			0.181	0.670	0.149	0.699	-
CAN-Milk	1st period	1983	1	1.918	0.166	0.001	0.975	-
	2nd period			0.008	0.927	0.002	0.966	-
UK-Milk	1st period	1984	1	0.008	0.806	0.187	0.666	-
	2nd period			0.073	0.787	0.139	0.710	-
DE-Milk	1st period	1975	2	0.018	0.893	0.159	0.690	-
	2nd period			0.010	0.920	1.014	0.314	-
US-Pork	1st period	1981	2	0.009	0.308	0.042	0.837	-
	2nd period			0.215	0.643	0.005	0.823	-
US States-Milk								
CA	1st period	1972	2	0.023	0.881	0.643	0.423	-
	2nd period			4.871	0.027	0.192	0.661	$\mathcal{P} \to \mathcal{E}$
ID	1st period	1976	1	0.002	0.734	0.906	0.341	-
	2nd period			14.494	0.000	0.020	0.887	$\mathcal{P} \to \mathcal{E}$
IL	1st period	1977	1	2.086	0.149	0.791	0.374	-
	2nd period			0.041	0.840	0.082	0.775	-
IN	1st period	1984	1	0.340	0.560	1.410	0.235	-
	2nd period			0.379	0.538	0.055	0.814	-

TABLE 10. Continued

State/ Commodity	Causality	Break Year	Number of lags p[a]	$\mathcal{P} \rightarrow \mathcal{E}$ χ^2-test	$\mathcal{P} \rightarrow \mathcal{E}$ p-value	$\mathcal{E} \rightarrow \mathcal{P}$ χ^2-test	$\mathcal{E} \rightarrow \mathcal{P}$ p-value	Conclusion
KY	1st period	1979	1	3.994	0.046	1.713	0.191	$\mathcal{P} \rightarrow \mathcal{E}$
	2nd period			0.030	0.862	0.002	0.969	-
MI	1st period	1967	1	0.030	0.863	0.345	0.557	-
	2nd period			1.003	0.316	0.137	0.712	-
MN	1st period	1982	2	0.209	0.648	0.069	0.793	-
	2nd period			0.114	0.735	1.301	0.254	-
NY	1st period	1976	1	0.059	0.808	3.219	0.073	$\mathcal{E} \rightarrow \mathcal{P}$
	2nd period			0.000	0.881	2.378	0.985	-
OH	1st period	1971	2	0.111	0.739	0.319	0.572	-
	2nd period			0.639	0.424	1.314	0.252	-
PA	1st period	1967	1	0.378	0.539	1.074	0.300	-
	2nd period			0.403	0.526	0.865	0.352	-
TX		None	2	0.054	0.817	1.373	0.241	-
VA	1st period	1972	1	0.001	0.817	0.002	0.961	-
	2nd period			14.409	0.000	0.271	0.603	$\mathcal{P} \rightarrow \mathcal{E}$
WA		None	3	0.068	0.794	0.028	0.867	-
WI	1st period	1974	1	0.129	0.719	1.315	0.252	-
	2nd period			0.159	0.207	1.237	0.266	-

Note: In this test, proceed by fitting a $VAR(p+d)$ in levels and apply a standard F-test involving the coefficients of lags 1 to p. The H_0 states that the parameters of lag 1 to p to the causal variable are zero.

[a] The optimal number of lags was chosen according to the Schwartz-Bayesian Information Criterion.

Looking at dairy in U.S. states in the lower part of Table 10, there are significant results in the causality test for California, Idaho, and Virginia in the second time regime and these regimes start around about 1974. As for Kentucky, the results indicate that productivity preceded $\mathcal{E}$ in the period leading up to 1979. The result for New York is quite distinct. Here we observe causality going from $\mathcal{E}$ to $\mathcal{P}$ during the first period, lasting until 1976.

Although the picture could be clearer, a possible interpretation of the results is as follows. Consistent with Proposition 1, during the 1930s through 1950s, technical progress was only made possible after production seasonality became sufficiently low so that return on capital exceeded the cost of capital. This interpretation is suggested by the U.S. milk result. Capital-intensive technology adoption then continued to the point where the high levels of installed capital required further endogenous changes in equilibrium production seasonality to be biased toward aseasonality. For dairy in U.S. states, evidence suggests that, from about 1970 onward, productivity growth fostered less seasonal agriculture. This is observed in California, Idaho, and Virginia. For Kentucky, and arguably also for Canada, this trend is observed during the first period. But as break points are estimated independently, it happens that the break point is relatively late in those two areas (1979 and 1983). Perhaps in these cases much of this causality has been captured in the first period and not the second. At variance with the other states is New York, where we observe causality from $\mathcal{E}$ to $\mathcal{P}$ in the first period. But again, this first period ends in 1976, and it may pick up a belated trend from the first period that we detected at the U.S. level in dairying.[8]

Corroborating evidence for conclusions in Table 10 is provided by Figure 1 and data on the capitalization of U.S. farms during the period 1935-45. During that wartime period, capital availability was extremely limited in the United Kingdom and the United States; capital on U.S. farms actually declined (Gardner 2002). And only in this period do we observe increases in seasonality in both the United States and the United Kingdom. In the 1980s, capital declined as well on U.S. farms during the farm crisis of that time, but deseasonalization of dairy production continued unabated. This suggests that the possible link between seasonality and capital depth has changed over these periods.

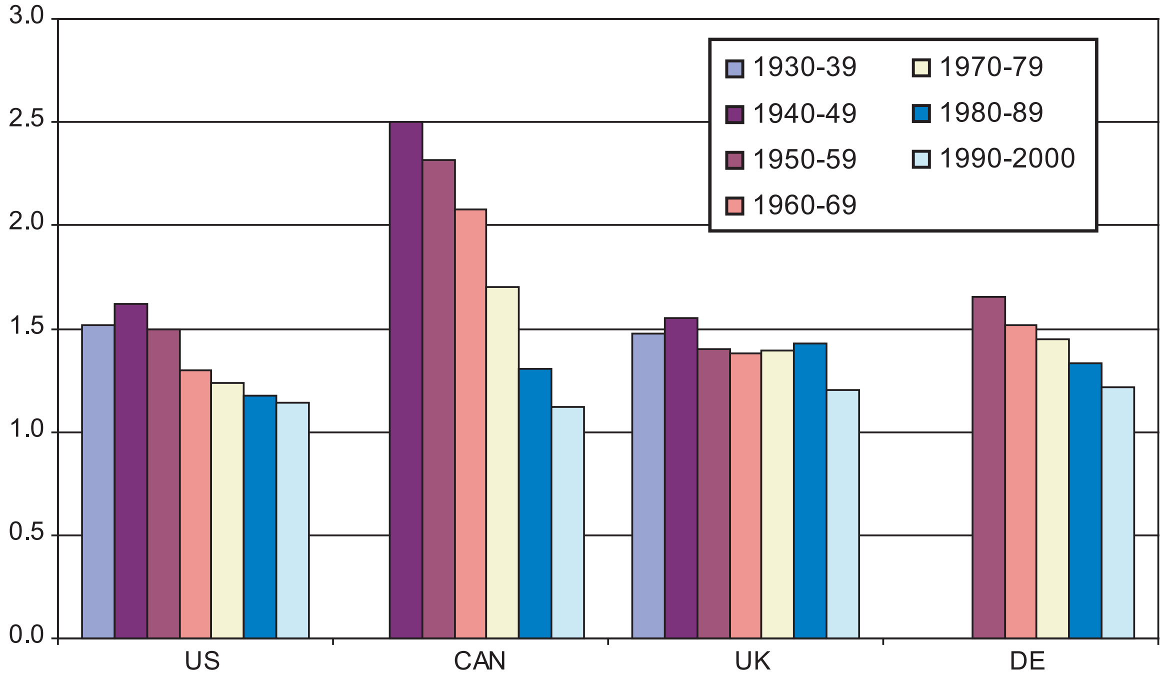

FIGURE 1. Changing peak-trough ratios of dairy production in selected countries

Discussion

Evidence presented provides qualified support for the hypothesis that deseasonalization was first necessary to induce productivity growth and only then did productivity growth precede lower seasonality. Placing our analysis in context with macroeconomic writing on industrialization, we note that industrial agriculture has adapted widely from manufacturing innovations. These adaptations have tended to be capital intensive, supporting the idea that spillovers from industrialization in other sectors can lay the foundations for an industrialized format in animal agriculture. A cause for delay may have been limited knowledge and control of animal biology, as reflected by the high level of production seasonality. Innovations surrounding bioengineering since the early 1950s may have removed this impediment.

An alternative hypothesis we cannot rule out without further data analysis is simultaneity, where both deseasonalization and productivity growth occur together.[9] One important limitation of our analysis is that the available time series are too short. In order to identify clearly the importance of deseasonalization early in the industrialization of animal production, time series have to start before WW II, and this type of data was available to us only for U.S. milk.

With the importance of aseasonality-induced productivity growth commencing in the late seventies or early eighties for most U.S. states, it would be interesting to find out if it arose directly through changes in production and processing technologies or through less direct routes. Agency and firm governance effects may have played a role. Sumner and Wolf (2002) use the 1993 Farm Cost and Returns Survey to discuss the impact of vertical integration on dairy production structure.[10] They show that the degree of vertical integration is much greater in U.S. Pacific states, the states that have taken production share from the traditional dairy regions of the Upper Midwest and Northeast over the past 30 years.

Endnotes

1. Jovanovic and Rousseau (2003) provide evidence in favor of growth in enterprise-dedicated capital used by U.S. corporations to motivate a theory on trends in the division of surplus.

2. Blayney (2002) provides detailed perspectives on recent U.S. production patterns.

3. For readers not familiar with modern capital-intensive dairy farming and processing, we reference Tamime and Law 2001, in which the extent and variety of commercial dairy mechanization and automation applications is documented. For on-farm U.S. agriculture in general, real net (of depreciation) on-farm investment was positive for most years between 1945 and 1980. A decline in real capital investment occurred only with the farm crises of the 1980s (for data, see p. 263 in Gardner 2002).

4. States were selected on the availability of continuous monthly production data over the 1950-2002 period. The chosen states represented 63 percent of U.S. production in 1950 and 75 percent of production in 2000.

5. An interesting comparison of structural divergence between California and Wisconsin systems over 1950-1982 is provided in Gilbert and Akor 1988, which shows that the systems have diverged markedly in farm structure and input usage patterns.

6. We would have liked to base this analysis on time series of equal length, which would have required restriction of the dates covered to the lowest common denominator. But the longest time series available in our sample reveals interesting results that differ from those exhibited by shorter time series, and we decided to use the maximum information available in our analysis.

7. Using cumulative sum and Chow test analyses, Erdogdu also found evidence of structural change in U.S. livestock production seasonality.

8. Remember that U.S. dairy data is available since 1930, but state-level data series commence in 1950. With the U.S. milk regime break in 1957, most of the data that identified $\mathcal{E} \rightarrow \mathcal{P}$ is not available at the state level. Indeed, at the U.S. level we find a second break in 1979, similar to the breaks identified across different U.S. states.

9. A theoretical foundation for the idea of simultaneity can be developed from equilibrium in systems with generalized complementarities. See Milgrom, Qian, and Roberts 1991 for a model identifying conditions supporting sequential directed adjustments in industry behavior that, as time intervals decline to zero, would support simultaneous adjustments.

10. The dairy states we analyzed do not coincide with those of the U.S. Department of Agriculture Farm Cost and Returns Survey as analyzed in Sumner and Wolf 2002. There, Georgia, Florida, Missouri, and Vermont are included, but Idaho, Illinois, Indiana, and Virginia are not.

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