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 Northern Hemisphere countries over the past 70 years. Using Irish farm-level data, we provide evidence that low seasonality favors laborsaving investments. We also suggest that (a) lower seasonality can be Granger-causally prior to increased productivity, and (b) productivity improvements can be Granger-causally prior to 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, dairy sector, Granger-causality, 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" accurately depict an animal production process for hogs, chickens, turkeys, and 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 routinized tasks. Field crop agriculture, on the other hand, though greatly affected by mechanization and other technological innovations, does not yet resemble an industrialized process. In this article we claim that how the use-specific nature of many investments in animal production interacts with seasonal variation in production costs is an important and overlooked detail in the evolution of agriculture. Put simply, variable cost motives for producing seasonally conflict with the motive to make capital sweat.

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 economic growth that consider the agriculture sector assume agriculture to be the reference non-industrial 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 (Mundlak 2000). Kuznets (1968) does emphasize 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.[1]

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. We refer the reader to Meeker 1999, to Boehlje 1996, or to Drabenstott 1994 on characterizations relevant to agriculture. The components that we are interested in are primarily 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 (e.g., Murphy, Shleifer, and Vishny 1989; 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 in these models relies on the assumption that firms face two technology choices where one is increasing 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 macro-economy 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 puzzle. Agricultural produce is largely commodity in character, and the market tends to be 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 cloth or pin manufacture, and so an explanation on the critical distinctions is warranted.

One theory is that agricultural industrialization is demand-led, through increasing demand by consumers and food retailers for product and process information (Barkema 1993; Drabenstott 1994). The demand-side story is best at explaining the change toward greater downstream control and increasing vertical coordination across many of the food sectors in high-income countries. 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. A processing firm is in a better position to do so when ownership or contract provisions enable it to supply inputs and specify production practices. In addition, monitoring costs suggest the processor would prefer to deal with a small number of high-volume producers that use common, routinized production methods. While likely a facet of the subject, for industrialized agriculture can deliver higher quality and more information, demand-side ideas have thus far explained little about the progress of industrialization. Demand-side arguments do not explain why crop agriculture is largely non-industrial. Nor do they identify common features in the technologies that tend to accompany industrialization. We conclude that some of the reasons for industrialization in an agricultural sector lie in the nature of the production process.

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 reasons 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 role of low variability in throughput and the role of enterprise-dedicated capital in enhancing productivity.

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 they are fed on. 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 largely solved these problems, though 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 will 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 will propose a theory on the origins of this deseasonalization, and on what it means for the industrialization of agriculture. This theory utilizes the broad insight in Allen and Lueck (2002) that irregularities in production matter in favoring one sort of input over another. In their model, it was proprietary labor over hired labor because the former is more strongly motivated to cope with irregularities. In our case, labor in general will be favored over capital when there is seasonality because labor is in general the more flexible input. We will also test aspects of this theory using two different data sets.

Our analysis is structured as follows. We first focus on dairying to 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 two brief models concerning the use of resources on farms facing different seasonal opportunities. Hypotheses emerge concerning temporal relationships between productivity and seasonality indices. 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 are 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 overwhelmingly in non-seasonal 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 the 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), 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 diet. These innovations have acted to alter seasonal costs. Final product storage innovations, 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 in 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 become shorter, 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. The tractor, N2, has proved to be just as versatile around the

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

Pro-seasonal	Seasonality Neutral	Anti-seasonal
Enhances competitiveness of grazing systems	*Versatile in use*	*Reduces role of nature*
P1. Electric fencing	N1. Genetic Innovation	A1. Artificial insemination
P2. Irrigation technologies	N2. Tractor	A2. Housing innovations
P3. Forage preservation innovations	*Reduces year-round costs*	*Use-dedicated capital*
Separates milk production from consumption	N3. Fertilization technologies	A3. Electricity in milking parlor
P4. Storage innovations for dairy output		A4. On-farm bulk handling technologies
		A5. Mechanized feed handling
		A6. Robotic milking machines
		A7. Downstream processing
		Mitigates problems with confinement
		A8. Manure handling methods
		A9. Antibiotics and sanitation technologies
		Limitations on labor flexibility
		A10. Specialization in alternative outputs
		A11. Feed transportations/storage innovations

farmyard as in the field and so the effect on the decision to confine cows is not immediate. Fertilization technologies have reduced the costs of concentrate feed, forage, and *in situ* grazing. In the absence of further information, we place it in the seasonality-neutral column.

The third column in Table 1 lists what we contend are anti-seasonal innovations. Artificial insemination and housing innovations have diminished the role of nature in animal production and must be important components of sector industrialization. Entries A3 through A7 are of particular interest in this paper and involve the growing capitalization of animal agriculture. As we will show, capital inflexibility should be important in determining the rate of deseasonalization. For all these entries, the equipment put in place is dedicated and is inelastic with respect to inter-season substitution.[3] Substitution of capital for labor facilitates the protection of quality when equipment speeds throughput and is easy to clean. In addition, automation generally complements the use of measurement technologies. This means that a more mechanized production approach may help a firm respond to more stringent quality specifications. Lower tolerance on waste emissions will also require that additional capital be installed to purify and store by-products so that additional environmental regulations may be anti-seasonal for animal production enterprises that are already largely confined.

Concerning entry A8, 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 non-seasonal production. Antibiotics, A9, are a substitute for sanitation. Although it is easier to monitor and maintain a health regime for a confined cow, cleanliness can be a problem and communicable disease can also be transmitted more quickly. Antibiotics and sanitation technologies help in this regard. Notice that investments in A8 and A9 also likely increase the stock of use-dedicated capital. Another factor is that U.S. farms have become increasingly specialized (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 in input markets, A11, are also likely to have been anti-seasonal, if only because feed and forage markets have become more integrated and so are less subject to regional effects.

The direct effects of aspects of these developments for agricultural productivity have been studied in detail in the technical literature on agriculture. Of interest to us are their effects on seasonal structure in animal production. In the next section we will 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 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

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.

level for hogs, milk, and beef, we use the Herfindahl index ($\mathcal{H}$) and the maximum 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 $\mathcal{E}_t = -\sum_{m=1}^{12} s_{m,t} \ln(s_{m,t})$ (Welsh 1988).[4] 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 1/12 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 in which production is maximum, $s_{\max,t}$, to production in the month in which 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 very similar and we conserve space by only reporting 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 milk production seasonality has declined over time. The most marked decline is in Canadian dairy production, which changed from a strongly seasonal system to an essentially non-seasonal 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 in pounds produced (for the United States) or head slaughtered (for Germany or the United Kingdom) is discernable.[5] Table 3b reports the seasonal indices for 14 major U.S. milk-producing states, in which monthly data were available from 1950 onwards.[6] The decline over time in seasonal dispersion is uniform across states.

An understanding of the table's regional dimension 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 2003. These states have had very different production systems, Wisconsin having smaller herds and more pronounced production seasonality. Since 1950, California has more than 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 15 percent. The less-significant midwestern states have lost production since 1950. New York has had a fairly stable production share while Pennsylvania has become a somewhat more prominent player. Southern states, small producers to begin with, have largely contracted while the parched western and mountain states have expanded.

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	1.52	1.49	1.24	1.14	2.4746	2.4759	2.4828	2.4842
CAN	–	2.32	1.70	1.12	–	2.4447	2.4699	2.4842
UK	1.48	1.40	1.39	1.21	2.4765	2.4791	2.4794	2.4833
DE	–	1.65	1.45	1.22	–	2.4708	2.4772	2.4829
Pork								
US	–	1.63	1.39	1.27	–	2.4728	2.4804	2.4824
UK	–	–	1.40	1.42	–	–	2.4788	2.4789
DE	–	1.30	1.16	1.22	–	2.4817	2.4839	2.4833
Beef								
US	–	1.29	1.22	1.21	–	2.4823	2.4833	2.4832
UK	–	–	1.57	1.83	–	–	2.4750	2.4708
DE	–	1.43	1.35	1.45	–	2.4784	2.4805	2.4785

[a]A decline in the peak-trough ratio represents a decline in the seasonality of production.
[b]A rise in the entropy 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	1.26	1.16	1.09	2.4818	2.4838	2.4846
ID	1.50	1.26	1.16	2.4754	2.4822	2.4836
IL	1.47	1.21	1.15	2.4773	2.4831	2.4837
IN	1.52	1.17	1.11	2.4755	2.4837	2.4843
KY	1.74	1.45	1.18	2.4647	2.4779	2.4834
MI	1.44	1.11	1.08	2.4786	2.4844	2.4846
MN	1.93	1.47	1.15	2.4613	2.4750	2.4835
NY	1.51	1.23	1.11	2.4751	2.4825	2.4844
OH	1.41	1.19	1.12	2.4782	2.4835	2.4841
PN	1.37	1.16	1.10	2.4802	2.4839	2.4844
TX	1.32	1.15	1.30	2.4804	2.4839	2.4808
VA	1.39	1.15	1.15	2.4778	2.4838	2.4840
WA	1.50	1.18	1.08	2.4761	2.4835	2.4846
WI	1.70	1.32	1.13	2.4697	2.4809	2.4841

[a] A decline in the peak-trough ratio represents a decline in the seasonality of production.
[b] A rise in the entropy index represents a decline in the seasonality of production.

TABLE 4. Dairy production shares by U.S. state and by decade, 1950-2003

State	1950	1960	1970	1980	1990	2003
CA	5.1	6.5↑[a]	8.1↑	10.6↑	14.2↑	23.8↑
ID	1.0	1.3↑	1.3↓	1.5↑	2.0↑	5.9↑
IL	4.5	3.4↓	2.4↓	2.0↓	1.7↓	1.4↓
IN	3.2	2.6↓	2.0↓	1.7↓	1.5↓	1.9↑
KY	2.1	2.1	2.1	1.7↓	1.5↓	1.0↓
MI	4.6	4.2↓	3.9↓	3.9	3.5↓	4.2↑
MN	6.9	8.4↑	8.2↓	7.4↓	6.8↓	5.5↓
NY	7.6	8.4↑	8.8↑	8.5↓	7.5↓	8.0↑
OH	4.5	4.3↓	3.8↓	3.4↓	3.2↓	3.0↓
PA	4.8	5.6↑	6.1↑	6.6↑	6.8↑	6.9↑
TX	3.0	2.4↓	2.6↑	2.8↑	3.7↑	3.8↑
VA	1.7	1.5↓	1.5	1.5	1.4↓	1.2↓
WA	1.5	1.5	1.8↑	2.3↑	3.0↑	3.7↑
WI	12.7	14.3↑	15.8↑	17.4↑	16.4↓	14.9↓

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

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 non-seasonal 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: $a_0 = (1-a_1)\bar{\mathcal{E}}$, i.e., whether constant geometric convergence to the non-seasonal 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

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

	a_0 (Std. error)[a]	a_1 (Std. error)	R^2	Durbin-Watson	p-value, $a_0 = (1 - a_1)\overline{\varepsilon}$
Milk					
UK	0.39**	0.84***	0.703	2.304	0.02
	(0.17)	(0.07)			
DE	0.20*	0.92***	0.888	2.338	0.09
	(0.12)	(0.05)			
CAN	0.06	0.98***	0.939	2.631	0.15
	(0.04)	(0.03)			
US	0.07	0.97***	0.940	2.632	0.30
	(0.07)	(0.03)			
Pork					
UK	1.23**	0.50**	0.212	2.044	0.01
	(0.48)	(0.19)			
DE	2.03***	0.18**	0.113	1.643	0.00
	(0.18)	(0.07)			
US	0.98***	0.61***	0.368	2.220	0.00
	(0.27)	(0.11)			
Beef					
UK	1.60***	0.35*	0.128	1.996	0.00
	(0.46)	(0.19)			
DE	9.12***	-2.82	0.034	1.028	0.07
	(5.00)	(2.02)			
US	2.2***	0.12	0.013	2.000	0.00
	(0.33)	(0.13)			

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

between 0.84 in the United Kingdom and 0.98 in Canada. Convergence rates are considerably lower, but still significant, for pork, where they vary between 0.18 in Germany and 0.61 in the United States. They are not significantly different from zero for beef in the United States and suggest time-series problems in Germany. Table 6 reports similar results for our set of 14 U.S. 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 0.78 and 0.93. 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 only have reliable indicators 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

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

State	a_0 (t-value)[a]	a_1 (t-value)	R^2	Durbin-Watson	p-value, $a_0 = (1-a_1)\overline{\mathcal{E}}$
CA	0.47*** (0.12)	0.81*** (0.05)	0.853	3.041	0.00
ID	0.36*** (0.11)	0.85*** (0.04)	0.886	2.361	0.00
IL	0.35** (0.14)	0.86*** (0.06)	0.820	2.423	0.01
IN	0.23*** (0.08)	0.91*** (0.03)	0.934	2.379	0.01
KY	0.32 (0.12)	0.87*** (0.05)	0.874	2.749	0.01
MI	0.23*** (0.06)	0.91*** (0.03)	0.962	2.087	0.00
MN	0.18 (0.11)	0.93*** (0.05)	0.894	2.799	0.12
NY	0.25* (0.09)	0.90*** (0.04)	0.928	2.741	0.01
OH	0.46*** (0.14)	0.82*** (0.05)	0.818	2.700	0.00
PA	0.27** (0.13)	0.89*** (0.05)	0.851	2.843	0.04
TX	0.56*** (0.17)	0.78*** (0.07)	0.714	2.086	0.00
VA	0.30*** (0.10)	0.88*** (0.04)	0.908	2.819	0.00
WA	0.27*** (0.06)	0.89*** (0.02)	0.964	2.659	0.00
WI	0.27*** (0.10)	0.89*** (0.04)	0.911	2.378	0.01

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

$\mathcal{P}$ in dairying. Measures of hog productivity in the growing phase are more difficult to obtain, and we use average litter size per farrowing sow as the productivity indicator $\mathcal{P}$.

Theoretical Motivation

Our intention is to explore interactions between productivity and seasonality over time. Table 7 shows correlations between (a) seasonality indicator $\mathcal{E}$, productivity indicator $\mathcal{P}$, and production share (we label it as $\mathcal{S}$) for the 14 U.S. states listed in Table 6. The correlations between $\mathcal{S}$ and $\mathcal{E}$, between $\mathcal{S}$ and $\mathcal{P}$, and between $\mathcal{E}$ and $\mathcal{P}$ were calculated based on 1950 data for the 14 states, and again on 2003 data. In 1950, when the high seasonality systems of the upper Midwest had the large shares in U.S. total production, a negative correlation existed between production shares and aseasonality.

TABLE 7. Correlation between production shares, seasonality, and productivity in 14 dairy states in 1950 and 2003

	$\mathcal{E}$		$\mathcal{P}$	
	1950	**2003**	**1950**	**2003**
S	-0.23	0.55	0.46	0.31
$\mathcal{E}$			0.19	0.75

This negative relationship turned into a strongly positive one in 2003 because by then the aseasonal western state production systems had large shares in U.S. production.

The relation between productivity and production shares is, as expected, positive in both periods but it declined from 0.46 in 1950 to 0.31 in 2003. This decline indicates that other factors are important. We look next at capital inflexibility as a motive for the closeness in relation between aseasonality and productivity in the lower right part of Table 7.[7] The relationship has always been positive for the dates covered but has become much stronger over the last 50 years, increasing from 0.19 in 1950 to 0.75 in 2003.

Model of Labor Intensity

Let a single gallon of output be produced across the two seasons in one year. Fraction $\theta > 0.5$ is produced in season B, and the remainder is produced in season A. Let P, r, and w be, respectively, output price, capital rental rate per year, and unit labor cost. The baseline labor requirement per gallon is λ units per hour while the baseline capital requirement is κ per gallon. The possibility exists of renting (investing) one additional unit of capital in order to reduce the labor requirement per gallon to $\alpha\lambda$, $0 \le \alpha < 1$. Recognizing labor flexibility and capital inflexibility, compare the baseline and investment scenarios. Table 8 summarizes the economic environment.

The baseline π^{BL} and investment π^{I} policy profits are as follows:

$$\begin{aligned}\pi^{BL} &= P - \max[\theta, 1-\theta] r\kappa - w\lambda = P - \theta r\kappa - w\lambda;\\ \pi^{I} &= P - \max[\theta, 1-\theta] r(\kappa+1) - w\alpha\lambda = P - \theta r(\kappa+1) - w\alpha\lambda.\end{aligned} \tag{2}$$

Notice that $\max[\pi^{BL}, \pi^{I}]$ is decreasing in the value of θ, so that profit is decreasing in seasonality index θ even after endogenizing the investment choice. Taking the difference, we have $\pi^{I} > \pi^{BL}$ if

TABLE 8. Profits by season and investment decision

	Labor required		Capital required	
	Season A	**Season B**	**Season A**	**Season B**
Baseline	$(1-\theta)\lambda$	$\theta\lambda$	$\theta\kappa$ (slack)	$\theta\kappa$
Investment	$(1-\theta)\alpha\lambda$	$\theta\alpha\lambda$	$\theta(\kappa+1)$ (slack)	$\theta(\kappa+1)$

$$\frac{(1-\alpha)\lambda}{\theta} > \frac{r}{w}. \tag{3}$$

As the value of θ declines toward the uniform production level of $\theta = 0.5$, then the threshold ceiling capital rental rate at which investment occurs increases toward $2(1-\alpha)\lambda w$. By contrast, if production is concentrated in one season only then the threshold ceiling capital rental rate is half the level, $(1-\alpha)\lambda w$.

Compare now factor uses under different θ levels. If $1 > (1-\alpha)\lambda w / r > 0.5$, then farms with θ close to 0.5 will invest while those with θ close to 1 will not. Investing farms use lower labor levels per gallon when averaged over the whole year, $\alpha\lambda$ and not λ. Investing farms will use $\theta(\kappa+1)$ capital per gallon. But we cannot be sure whether this is larger or smaller than capital per gallon for non-investing farms because the only exogenous feature distinguishing the farms is the lower value of θ that motivates investment. Consider two farms, H and L, with respective seasonality parameters θ_H and θ_L where $1 \geq \theta_H > (1-\alpha)\lambda w / r > \theta_L \geq 0.5$. This set of inequalities, which is the only information available, cannot clarify whether $\theta_L(\kappa+1)$ is larger than $\theta_H\kappa$. Examples are readily constructed such that $\theta_L(\kappa+1) > \theta_H\kappa$ and such that $\theta_L(\kappa+1) < \theta_H\kappa$. Under lower seasonality, the need to use capital that meets peak demand falls but the incentive to make a labor-saving investment increases. We summarize the positive finding above as follows:

PROPOSITION 1. *Profit increases and labor used per gallon declines when production seasonality declines.*

Model of Total Productivity

Stepping away from labor substitution, we develop a slightly different two-season model that looks at the amount of fixed cost capital a farm is willing to bear in order to reduce marginal costs of any sort. A representative farm produces animal output in two seasons; season A is high-cost while 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 $\overline{c}$, and this unit cost parameter will change as a result of technical innovations. These costs amount to $\overline{c}q_A + \overline{c}q_B$ per annum. Finally, there are per annum peak-load unit capital costs amounting to $F\max[q_A, q_B]$. As with $\overline{c}$, 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. Firm annual profit is then

$$\pi = (P - \overline{c}) \times (q_A + q_B) - c_A q_A - c_B q_B - C(q_A, q_B) - F\max[q_A, q_B]. \tag{4}$$

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 $(c_A - c_B)(q_A^* - q_B^*) \le 0$, 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 items A2 through A8 in Table 1. The innovation will be adopted if the trade-off between costs is sufficiently favorable. Applying the envelope theorem to (4), profit-increasing innovations are ones that satisfy
$\partial\overline{c} / \partial F \le -q_B^* / (q_A^* + q_B^*)$.

Now suppose that some set of incremental investment opportunities is available to the grower. These opportunities vary according to their trade-off between fixed and variable costs. Those that decrease $\overline{c}$ by a small amount $\Delta\overline{c}$ and increase F by a small amount ΔF with $\Delta\overline{c} < (\Delta F) q_B^* / (q_A^* + q_B^*)$ will not be adopted because they will decrease annual profit. All opportunities satisfying $\Delta\overline{c} \ge (\Delta F) q_B^* / (q_A^* + q_B^*)$ will be adopted. The threshold $(\Delta F)q_B^* / (q_A^* + q_B^*)$ is smallest at $0.5(\Delta F)$, when q_B^* declines to value q_A^* and production becomes non-seasonal. It is largest at ΔF, when $q_A^* = 0$.

PROPOSITION 2. *As seasonality decreases, that is, the peak-trough ratio decreases, then 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 one should see a pick-up in the adoption of capital-intense innovations that are already available to dairy producers. Alternatively, viewing Table 3b, one can take a regional perspective to conclude that the Wisconsin and Minnesota seasonal production systems should be less capital intensive than the California system. The proposition is also suggestive of a relationship between lower seasonality and greater vertical coordination in production. Suppose that the grower sells to just one processor, and alternative sales outlets are not as profitable. As use-dedicated capital intensity increases under lower seasonality, then quasi-rents (due to sunk capital) increase and the grower becomes more vulnerable to hold-up by the processor. If contracts are not sufficient to secure protection then vertical integration may become a more attractive production arrangement.[8]

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

$$\frac{q_B^*}{q_A^*} = \left(\frac{P - \overline{c} - c_B - F}{P - \overline{c} - c_A} \right)^{1/(\rho - 1)}, \tag{5}$$

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. The farm would not produce more in season A either because $c_B < c_A + F$. So $q_A^* = q_B^*$ when $c_A \le c_B + F$.

Differentiate (5) with respect to F, taking into account the associated change in $\overline{c}$, $d\overline{c} / dF < 0$, to obtain

$$\frac{d(q_B^* / q_A^*)}{dF}\Big|_{\overline{c}\ changes} = \frac{1}{\rho - 1}\left(\frac{P - \overline{c} - c_B - F}{P - \overline{c} - c_A}\right)^{(2-\rho)/(\rho-1)} \frac{c_A + \overline{c} - P + (c_A - c_B - F)d\overline{c} / dF}{(P - \overline{c} - c_A)^2}. \quad (6)$$

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 3. *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* $\overline{c}$ *decreases by a sufficient amount 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 capital-intensity-induced productivity growth should precede deseasonalization. It is not a contradiction of Proposition 2 because there can be mutually re-enforcing feedback between the levels of seasonality and productivity. 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 would expect to see deseasonalization before capital-intensity-induced productivity growth in order to establish a capital base in the production system.

CLAIM 4. *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 Labor Intensity and Seasonality

In order to test for the labor substitution hypothesis in Proposition 1, we obtained data on milk production in the Republic of Ireland. Grass grows well under Ireland's moist, cool climate, and especially on the richer soils of Munster and South Leinster. Surplus summer grass is conserved as silage or hay for winter feed, but some grain-based supplements are also fed throughout the year. The data set we use is farm-level for farms surveyed under the European Union's Farm Accounting Data Network (FADN).[9] Production data used to establish the seasonality index are recorded monthly, but all other data used are annual. Data availability was restricted to the period 1998-2003 because monthly data on earlier years are not available electronically. The observations used were the farms with complete, relevant information that were in the "Dairying" (meaning at least 66 percent of gross margin from dairying and about 40 percent of observations) or "Dairying/Other" farm systems.

Absent information to distinguish between the two types of capital, direct evidence on the role of seasonality in automation decisions can only be obtained from a regression of labor used per gallon on farm production seasonality and conditioning factors. For each year, we ran the ordinary least squares regression

$$Lab/Q = \beta_0 + \beta_1 \mathcal{E} + \beta_2 Q + \beta_3 S + \sum\nolimits_{i=3}^{8} \beta_{i+1} R_i, \tag{7}$$

where Q is farm output in 111,000 liters and Lab/Q is annual labor used per 100,000 liters of milk output. Regressor $\mathcal{E}$ is the entropy index as previously discussed. Regressor S is a dummy variable with value 0 for the "Dairying" system and value 1 for the "Dairying/Other" system. The R_i are regional dummy variables. There are eight regions comprised of groupings of one to six counties. Region 1 has been excluded to avoid dummy variable dependence, while region 2 (County Dublin only) is of negligible importance in milk production and its surveyed farms have been merged with the surrounding region (region 3). Results are provided in Table 9.

The results provide some evidence to suggest, in years 1999 through 2002 at any rate, that larger farms tended to be more labor efficient. This may be due to labor indivisibilities and scale economies in such laborsaving investments as milking technologies.

TABLE 9. Results of FADN data, Ireland

	1998	1999	2000	2001	2002	2003
Constant	67.40***	19.08***	17.15***	21.63***	3.20***	86.26***
	(6.67)[a]	(1.00)	(1.36)	(3.43)	(0.46)	(8.84)
ε	-27.96***	-7.09***	-6.38***	-7.57***	-0.73***	-37.97***
	(2.97)	(0.42)	(0.57)	(1.44)	(0.19)	(3.77)
Q	0.26	-0.61***	-0.49***	-0.58	-0.10***	0.81
	(0.42)	(0.06)	(0.14)	(0.41)	(0.24)	(0.67)
R3 (incl.	-1.04	-0.38	-0.16	-2.07	-0.61**	1.81
County Dublin)[b]	(2.06)	(0.36)	(0.76)	(2.17)	(0.25)	(3.66)
R4	-4.68**	-0.57	-1.11	-2.65	-0.76***	-2.44
	(1.96)	(0.40)	(0.68)	(1.93)	(0.27)	(3.98)
R5	-5.82***	-1.26***	-0.96	-2.73	-0.76***	8.01**
	(1.52)	(0.31)	(0.62)	(1.70)	(0.23)	(4.03)
R6	-4.66***	-0.88***	-1.31**	-3.40**	-0.81***	-2.35
	(1.42)	(0.29)	(0.60)	(1.56)	(0.24)	(3.14)
R7	-5.15***	-0.84***	-1.20**	-3.62**	-0.71***	-4.03
	(1.43)	(0.26)	(0.55)	(1.53)	(0.20)	(2.92)
R8	-3.00*	-0.53	0.96	-2.84	-0.74**	0.13
	(1.69)	(0.34)	(0.73)	(1.96)	(0.29)	(4.51)
S,	0.85	0.26	0.64*	1.73	0.41***	1.75
0 for 'Dairying'	(0.95)	(0.18)	(0.35)	(1.08)	(0.13)	(2.07)
Total number of observations	375	441	450	437	465	442
R^2	23.1	50.0	31.9	9.7	15.5	22.2

[a] *, **, and *** identify significance at the 10%, 5%, and 1% levels, respectively.
[b] The regions are R1 (Border counties): Louth, Leitrim, Sligo, Cavan, Donegal, Monaghan; R2: Dublin; R3 (East): Kildare, Meath, Wicklow; R4 (Midlands): Laois, Longford, Offaly, Westmeath; R5 (Midwest): Clare, Limerick, Tipperary North Riding; R6 (Southeast): Carlow, Kilkenny, Wexford, Tipperary South Riding, Waterford; R7 (Southwest): Cork, Kerry; R8 (West): Galway, Mayo, Roscommon.

The milk production effect is of some relevance to policy because Irish dairy farms have been constrained by an annual production quota since 1984 and quota transfer has been severely restricted. It is very likely that some farms would expand scale, and at lower output price levels, if free to do so (Glanbia 2004). The regressions suggest that these farms would be less seasonal in their output profile. For all years, the entropy coefficient is negative and significant at the 1 percent level. These coefficients provide strong evidence in favor of our Proposition 1, that labor per gallon declines as seasonality declines.

Empirical Relationships between Total Productivity and Seasonality

In Propositions 2 and 3 we 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, $\mathrm{Cov}(\mathcal{E},\mathcal{P})$ in Table 7 warrants further scrutiny. We test for Granger-causality in Northern Hemisphere milk production data. Granger-causality tests whether changes in one time series contain information that can be used to forecast changes in another time series. It is not a statistical test of true causation. But the absence of Granger-causation would cast doubt on the validity of a hypothesis of true causation and so would provide additional evidence for consideration by the informed reader.

Since the work of Yule (1926), the danger of spurious regressions in testing for relations 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 Granger-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 will first test for unit roots and cointegration.

Stationarity Tests

Using the Dickey-Fuller procedure we test for the 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 $\mathcal{E}$ at both the country and U.S. state levels are reported in Table 10. The table shows the test statistics, followed by the p-value in parentheses and the number of lags used in brackets.

The test results are quite mixed and we cannot reject a unit root in most cases.[10] For German milk and U.S. pork, the null of a unit root in $\mathcal{E}$ is rejected according to both augmented Dickey-Fuller and Phillips-Perron tests. For all states, evidence is inconclusive

TABLE 10. 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	- 2.85 (0.18)* [10]	- 9.72 (0.46) [10]	- 1.48 (0.84) [2]	- 2.28 (0.96) [2]
CAN-Milk	0.14 (1.00) [3]	- 4.58 (0.85) [3]	- 0.33 (0.99) [2]	- 0.93 (0.99) [2]
UK-Milk	- 2.14 (0.52) [2]	- 17.96 (0.11) [2]	- 1.61 (0.79) [2]	- 14.28 (0.21] [2]
DE-Milk	- 3.67 (0.02) [2]	- 31.36 (0.01) [2]	- 0.91 (0.96) [5]	- 4.12 (0.88) [5]
US-Pork	-4.74 (0.00) [10]	- 37.06 (0.00) [10]	0.05 (1.00) [2]	- 1.91 (0.97) [2]
U.S. States-Milk				
CA	- 3.95 (0.01) [2]	- 13.26 (0.25) [2]	- 3.06 (0.12) [2]	- 29.26 (0.01) [2]
ID	- 2.31 (0.43) [3]	- 18.30 (0.10) [3]	- 0.55 (0.98) [4]	- 1.33 (0.98) [4]
IL	- 0.57 (0.98) [5]	- 9.18 (0.49) [5]	- 0.74 (0.97) [2]	- 2.42 (0.96) [2]
IN	- 4.59 (0.00) [5]	- 2.62 (0.95) [5]	- 0.70 (0.97) [3]	- 2.98 (0.94) [3]
KY	- 0.82 (0.96) [3]	- 17.49 (0.12) [3]	- 1.41 (0.86) [5]	- 23.59 (0.03) [5]
MI	- 6.23 (0.00) [4]	- 3.65 (0.91) [4]	- 2.25 (0.99) [2]	- 1.84 (0.97) [2]
MN	- 1.42 (0.86) [5]	- 24.59 (0.03) [5]	- 1.53 (0.82) [2]	- 5.58 (0.78) [2]
NY	- 2.22 (0.48) [5]	- 7.76 (0.60) [5]	- 1.81 (0.70) [2]	- 7.40 (0.63) [2]
OH	- 5.97 (0.00) [5]	- 7.92 (0.59) [5]	- 2.66 (025) [2]	- 16.32 (0.15) [2]
PA	- 0.40 (0.99) [4]	- 10.05 (0.43) [4]	- 2.23 (0.48) [2]	- 7.96 (0.59) [2]
TX	- 4.24 (0.06) [2]	- 10.86 (0.38) [2]	- 2.65 (0.26) [2]	- 20.97 (0.06) [2]
VA	- 0.70 (0.97) [3]	- 4.25 (0.87) [3]	- 0.99 (0.95) [2]	- 5.72 (0.77) [2]
WA	- 3.56 (0.00) [4]	- 6.35 (0.72) [4]	- 3.39 (0.05) [2]	- 10.43 (0.41) [2]
WI	- 4.22 (0.00) [5]	- 8.41 (0.55) [5]	- 2.10 (0.54) [2]	- 10.00 (0.44) [2]

Note: Numbers in parentheses are p-values; those in brackets are lags.

on the existence of a unit root in ε. While it is rejected according to the augmented Dickey-Fuller (Phillips-Perron) test in California, Indiana, Michigan, Ohio, Texas, Washington, and Wisconsin (Idaho and Minnesota), it is then accepted under the other test. The existence of a unit root in the productivity series is rejected at the 10 percent level according to the Phillips-Perron test in California, Kentucky, and Texas, and according to the augmented Dickey-Fuller test in Washington.

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 11. The results obtained using the Engle-Granger method suggest that the productivity and seasonality series may be cointegrated in Kentucky, Pennsylvania, Texas, 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 (rank of the characteristic roots equal to zero) for milk in the United Kingdom, California, Illinois, Ohio, Pennsylvania, Washington, and Wisconsin. As will be explained, the way in which causality tests are conducted depends on the presence of integrated and/or cointegrated series.

Granger 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

TABLE 11. Johansen and Engel-Granger cointegration tests

	Johansen[a] Trace Statistic		Dep. Var.	Engel–Granger[b] (H_0: no cointegration) t-test	p-value	
US-$\mathcal{E}$-Milk	12.84 (0.24)	[1]	US-Milk-$\mathcal{E}$	-2.80	0.36	[10]
			US-Milk-$\mathcal{P}$	-0.49	0.99	[7]
CAN-$\mathcal{E}$	12.70 (0.25)	[1]	CAN-Milk-$\mathcal{E}$	-2.04	0.75	[2]
			CAN-Milk-$\mathcal{P}$	-2.11	0.72	[2]
UK-$\mathcal{E}$	21.88 (0.02)	[1]	UK-Milk-$\mathcal{E}$	-3.08	0.23	[4]
			UK-Milk-$\mathcal{P}$	-2.83	0.35	[10]
DE-$\mathcal{E}$	15.81 (0.11)	[1]	DE-Milk-$\mathcal{E}$	- 3.04	0.25	[4]
			DE-Milk-$\mathcal{P}$	- 1.97	0.79	[6]
US-$\mathcal{E}$-Pork	13.26 (0.22)	[10]	US-Pork-$\mathcal{E}$	-1.56	0.91	[10]
			US-Pork-$\mathcal{P}$	-1.67	0.88	[7]
US-States (milk only)						
CA-$\mathcal{E}$	27.42 (0.00)	[1]	CA-$\mathcal{E}$	- 2.83	0.34	[2]
			CA-$\mathcal{P}$	- 3.23	0.18	[2]
ID-$\mathcal{E}$	11.53 (0.34)	[1]	ID-$\mathcal{E}$	- 2.90	0.31	[2]
			ID-$\mathcal{P}$	- 1.90	0.81	[2]
IL-$\mathcal{E}$	26.66 (0.00)	[1]	IL-$\mathcal{E}$	- 1.62	0.89	[5]
			IL-$\mathcal{P}$	- 1.82	0.84	[2]
IN-$\mathcal{E}$	7.95 (0.65)	[1]	IN-$\mathcal{E}$	- 3.34	0.14	[2]
			IN-$\mathcal{P}$	- 1.52	0.92	[3]
KY-$\mathcal{E}$	11.34 (0.36)	[4]	KY-$\mathcal{E}$	- 1.13	0.97	[3]
			KY-$\mathcal{P}$	- 3.96	0.03	[2]
MI-$\mathcal{E}$	12.21 (0.29)	[1]	MI-$\mathcal{E}$	- 2.30	0.63	[2]
			MI-$\mathcal{P}$	- 1.27	0.96	[2]
MN-$\mathcal{E}$	8.72 (0.59)	[2]	MN-$\mathcal{E}$	- 2.68	0.42	[5]
			MN-$\mathcal{P}$	- 2.38	0.59	[2]
NY-$\mathcal{E}$	11.89 (0.31)	[1]	NY-$\mathcal{E}$	- 1.71	0.87	[2]
			NY-$\mathcal{P}$	- 2.01	0.77	[2]
OH-$\mathcal{E}$	19.10 (0.04)	[0]	OH-$\mathcal{E}$	- 1.54	0.91	[5]
			OH-$\mathcal{P}$	- 2.72	0.40	[2]
PA-$\mathcal{E}$	17.42 (0.06)	[2]	PA-$\mathcal{E}$	- 2.99	0.27	[2]
			PA-$\mathcal{P}$	- 3.57	0.08	[2]
TX-$\mathcal{E}$	13.93 (0.18)	[4]	TX-$\mathcal{E}$	- 3.58	0.08	[2]
			TX-$\mathcal{P}$	- 2.74	0.39	[2]
VA-$\mathcal{E}$	13.15 (0.23)	[1]	VA-$\mathcal{E}$	- 1.39	0.94	[3]
			VA-$\mathcal{P}$	- 1.77	0.86	[2]

TABLE 11. Continued

	Johansen[a] Trace Statistic		Dep. Var.	Engel–Granger[b] (H_0: no cointegration) t-test	p-value	
WA-$\mathcal{E}$	25.71 (0.01)	[2]	WA-$\mathcal{E}$	- 2.15	0.71	[2]
			WA-$\mathcal{P}$	- 3.56	0.09	[2]
WI-$\mathcal{E}$	23.01 (0.01)	[0]	WI-$\mathcal{E}$	- 2.91	0.31	[2]
			WI-$\mathcal{P}$	- 2.95	0.29	[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 cointegrating vectors (p>0). The p-value is reported in parentheses. The optimal lag length has been 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 has been chosen using the Akaike-Information Criterion and is indicated in brackets.

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 statistical causality, first 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

$$\begin{pmatrix} \mathcal{E}_{j,t} \\ \mathcal{P}_{j,t} \end{pmatrix} = \begin{pmatrix} a_0 \\ b_0 \end{pmatrix} + \begin{pmatrix} a_{11}^j & \cdots & a_{1p}^j & a_{1p+1}^j & \cdots & a_{1p+d}^j & b_{11}^j & \cdots & b_{1p}^j & b_{1p+1}^j & \cdots & b_{1p+d}^j \\ a_{21}^j & \cdots & a_{2p}^j & a_{2p+1}^j & \cdots & a_{2p+d}^j & b_{21}^j & \cdots & b_{2p}^j & b_{2p+1}^j & \cdots & b_{2p+d}^j \end{pmatrix} \begin{pmatrix} \mathcal{E}_{j,t-1} \\ \vdots \\ \mathcal{E}_{j,t-p} \\ \mathcal{E}_{j,t-p-1} \\ \vdots \\ \mathcal{E}_{j,t-p-d} \\ \mathcal{P}_{j,t-1} \\ \vdots \\ \mathcal{P}_{j,t-p} \\ \mathcal{P}_{j,t-p-1} \\ \vdots \\ \mathcal{P}_{j,t-p-d} \end{pmatrix} \tag{8}$$

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 $a_{\cdot\cdot}^j$ and $b_{\cdot\cdot}^j$ 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 Granger-cause productivity gains, $H_0 : a_{21} = a_{22} = ... = a_{2p} = 0$ should be rejected. For productivity gains to Granger-cause deseasonalization, $H_0 : b_{11} = b_{12} = ... = b_{1p} = 0$ should be rejected.

As to the formal test of equation (8), 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 likely is unrealistic and structural breaks in at least one parameter are probable. A classical testing procedure for structural change is based on Chow's test (1960), 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 test's main limitation 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 equation (8), 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 whole sample log quasi-likelihood 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 (1996) to test for Granger causality.

Results for sovereign countries and U.S. states are presented in Table 12. The first column indicates the country/state and commodity. For each pair, but with two exceptions, tests are performed on two periods. The exceptions are US-Milk and CA-Milk, for which two breaks were detected. 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.[11] The fourth column in Table 12 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 of Table 12. Columns 5 and 6 report the test statistics and respective p-values on the test that productivity growth Granger-causes 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 Granger causality), or that neither hypothesis is accepted (no Granger causality). To help the reader in interpreting the results, we include a final column indicating any detected Granger-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.[12] 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.

Looking at dairy in the U.S. states in the lower part of Table 12, there are significant results in the causality test for Idaho, Minnesota, and Texas in the second time regime and these regimes start in 1968-76. In Texas, deseasonalization precedes productivity growth while the order is reversed in the more northern states. In two states, results

TABLE 12. Dolado and Lütkepohl causality test for aseasonality and productivity

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
Countries								
US-Milk	1st period	1957, 1979	1	0.23	0.63	2.79	0.10	$\mathcal{E} \rightarrow \mathcal{P}$
	2nd period			0.18	0.67	0.25	0.62	-
	3rd period			0.01	0.91	0.08	0.72	-
CAN-Milk	1st period	1983	1	1.92	0.17	0.00	0.98	-
	2nd period			0.01	0.93	0.00	0.97	-
UK-Milk	1st period	1984	1	0.01	0.81	0.19	0.67	-
	2nd period			0.07	0.79	0.14	0.71	-
DE-Milk	1st period	1975	2	0.02	0.89	0.16	0.69	-
	2nd period			0.01	0.92	1.72	0.19	-
US-Pork	1st period	1981	2	0.01	0.31	0.04	0.84	-
	2nd period			0.22	0.64	0.01	0.82	-
US-States Milk								
CA	1st period	1971, 1987	1	3.77	0.05	0.00	0.96	$\mathcal{P} \rightarrow \mathcal{E}$
	2nd period			0.27	0.60	0.02	0.89	-
	3rd period			0.96	0.33	0.01	0.93	-
ID	1st period	1976	1	0.54	0.46	0.91	0.34	-
	2nd period			11.11	0.00	0.03	0.87	$\mathcal{P} \rightarrow \mathcal{E}$
IL	1st period	1975	2	0.15	0.66	0.47	0.49	-
	2nd period			0.23	0.34	0.03	0.86	-
IN	1st period	1981	1	0.32	0.57	1.47	0.23	-
	2nd period			0.78	0.38	0.00	0.97	-

TABLE 12. Continued

State/ Commodity				$\mathcal{P} \rightarrow \mathcal{E}$		$\mathcal{E} \rightarrow \mathcal{P}$		
Countries	**Causality**	**Break Year**	**Number of lags p[a]**	χ^2 **-test**	**p-value**	χ^2 **-test**	**p-value**	**Conclusion**
KY	1st period	1983	1	7.71	0.01	0.01	0.93	$\mathcal{P} \rightarrow \mathcal{E}$
	2nd period			0.00	0.99	0.38	0.54	-
MI	1st period	1968	1	0.06	0.81	0.47	0.49	-
	2nd period			1.04	0.31	0.39	0.53	-
	1st period	1968	1	1.05	0.31	0.15	0.70	-
	2nd period			5.81	0.02	0.42	0.52	$\mathcal{P} \rightarrow \mathcal{E}$
NY	1st period	1978	1	0.01	0.95	5.35	0.02	$\mathcal{E} \rightarrow \mathcal{P}$
	2nd period			0.13	0.72	0.60	0.44	-
OH	1st period	1971	2	0.11	0.74	0.32	0.57	-
	2nd period			0.93	0.33	1.37	0.24	-
PA	1st period	1967	1	0.38	0.54	1.07	0.30	-
	2nd period			0.34	0.56	0.83	0.36	-
TX	1st period	1969	1	0.01	0.94	0.00	0.96	-
	2nd period			1.54	0.22	5.76	0.02	$\mathcal{E} \rightarrow \mathcal{P}$
VA	1st period	1972	1	0.05	0.82	0.00	0.96	-
	2nd period			2.02	0.16	0.10	0.31	-
WA	1st period	1975	1	0.03	0.85	1.95	0.16	-
	2nd period			0.02	0.88	1.70	0.19	-
WI	1st period	1974	2	0.08	0.78	1.08	0.30	-
	2nd period			0.01	0.94	0.03	0.85	-

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.

indicate that productivity preceded deseasonalization earlier in last half of the twentieth century, to 1971 in California and to 1983 in Kentucky. The result for New York is quite distinct. Here we observe Granger causality going from $\mathcal{E}$ to $\mathcal{P}$ during the first period, lasting until 1978.

Although the picture could be clearer, a possible interpretation of the results goes as follows. Consistent with Proposition 2, during 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 dairying in U.S. states, evidence suggests that, from about 1950 onward, productivity growth tended to foster less seasonal agriculture.[13]

Suggestive information is provided by Figure 1, together with 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. Capital stock declined as well on U.S. farms during the farm crises of the 1980s, but deseasonalization of dairy production continued unabated. This suggests that the possible link between seasonality and capital depth has changed over these periods. Furthermore, any role that deseasonalization may have had in eliciting productivity growth may have occurred just after World War II.

Discussion

This paper has provided strong statistical evidence that production seasonality has declined in many sectors of animal agriculture in North America and northern Europe over the 1930-2003 period. We have provided a simple theory to rationalize these empirical observations, namely, that capital is used most effectively when production seasonality is low. The theory provides two testable hypotheses. One is that high production seasonality should be associated with high labor factor intensity. Using farm-level data for Ireland over the years 1998-2003, we find strong evidence in favor of this

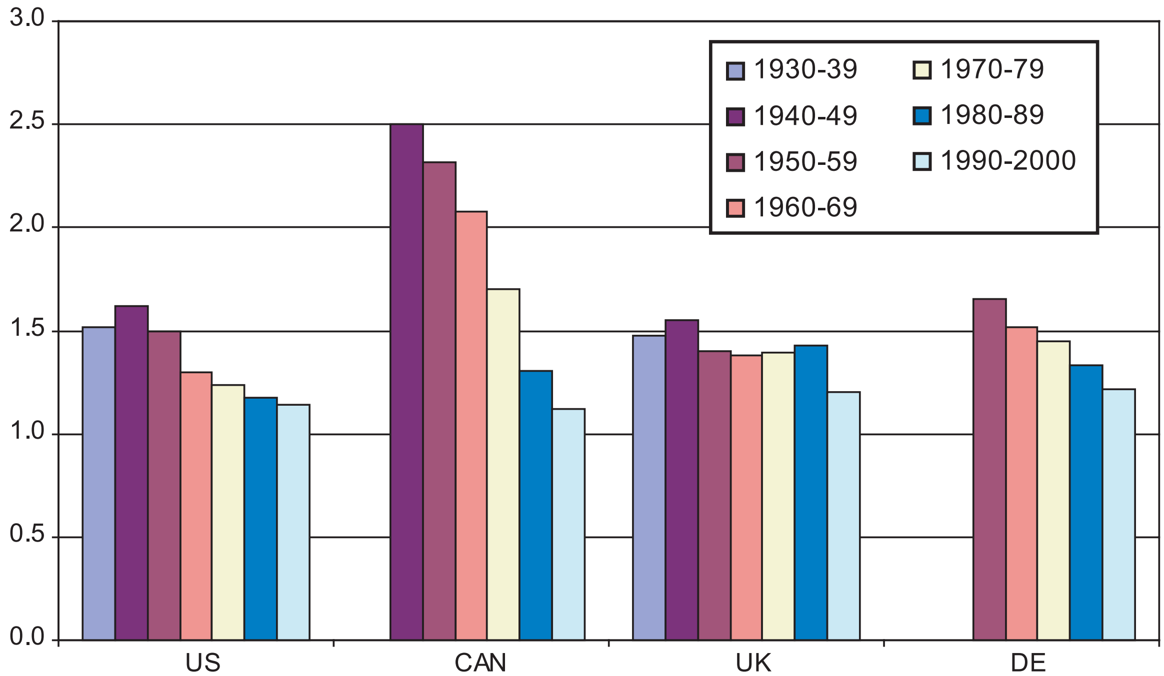

FIGURE 1. Changing peak-trough ratios of dairy production in selected countries

hypothesis. A second hypothesis is that deseasonalization is first necessary to induce productivity growth, and only then should productivity growth precede lower seasonality. We find some support for this hypothesis.

Placing our second hypothesis 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 on 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.

One important limitation of our analysis is that the available time series are too short. To identify clearly the importance of deseasonalization early in the industrialization of animal agriculture, time series have to start before World War II and we were only able to obtain this type of data for U.S. milk. More and better data are needed in order to be more confident about why animal agriculture is becoming less seasonal.

Endnotes

1. Studies in economic history have shown evidence that agricultural seasonality should have a negative impact on the rate of non-agricultural industrialization and on productivity outside agriculture. This is because industrial plants are most efficient when labor supply is constant (Sokoloff and Dollar 1997; Sokoloff and Tchakerian 1997). Our interest is not in the role of agricultural seasonality on the productivity and industrialization of external industries but on the productivity and industrialization of agriculture itself.

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

3. Hank van Exel, a dairy farmer with 1,600 cows in the California Central Valley, has rationalized (as quoted in Stuller and Schofield 1999) his decision to expand as follows: "Might as well. We own our feed truck and every hour it sits unused, we lose money on the investment. There's an incentive to make use of everything, all of the time." 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 outlined. 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. In a probablistic setting, rather than our setting of mass weights, $\ln(s_{m,t})$ may be thought of as an index of surprise that event m occurred at time t. Physicists like to think about the entropy of energy as the amount of disorder in a system. Heat friction reflects disorder because energy is lost to the external environment. In our case, if all production is in one month, then production is very ordered and $\varepsilon_t = 0$. If production is uniform across months, then ε_t reaches its maximum value at $\ln(12) = 2.4849$ and the system is in complete disorder.

5. Cattle require more time to mature than do hogs, while age at maturity varies considerably by sex, breed, and feeding regime. These natural variations are further accentuated by weather and feed availability when animals are pasture fed. In addition, breeding stock and dairy stock make larger contributions to beef production than to production of other species. For these reasons, the correlation between birth month and slaughter month is likely to be less strong for cattle than for other husbanded species.

6. States were selected on the availability of continuous monthly production data over 1950-2003. The chosen states represented 63 percent of U.S. production in 1950 and 85 percent of production in 2003.

7. We recognize the likelihood that other factors are also influential. For example, supply control policies of one form or another have been imposed in all of the dairy sectors we consider. In some cases, as in the European Union after the 1984 dairy quota (annual) program was imposed, impediments to the transfer of production rights have limited scale expansion. Non-transferrability will reduce the rate of deseasonalization if larger-scale operations tend to be less seasonal.

8. We thank a reviewer for this insight on connecting facets of agricultural industrialization. Sumner and Wolf (2002) use the 1993 Farm Cost and Returns Survey to discuss the impact of vertical integration on dairy production structure. They show that the degree of vertical integration is much larger in the U.S. Pacific states, the states that have taken production share from the traditional dairy regions of the Upper Midwest and Northeast in the past 30 years.

9. A summary of the data is provided in Teagasc's National Farm Survey of 2003; see http://www.teagasc.ie/publications/2004/20040809.htm (as viewed on 11/24/2004).

10. However, both tests are generally recognized to be of low power.

11. We would have liked to base this analysis on time series of equal length, and this would require us to restrict 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.

12. Using cumulative sum and Chow test analysis, Erdogdu (2002) also found evidence of structural change in U.S. livestock production seasonality.

13. 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.

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