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TIME-SERIES MODEL WITH PERIODIC STOCHASTIC REGIME SWITCHING

Part II: Applications to 16th- and 17th-Century Grain Prices

CATHERINE BAC
DREES

JEAN-MICHEL CHEVET
INRA—HEDM

ERIC GHYSELS
University of North Carolina, Chapel Hill
and
Centre Interuniversitaire de Recherche en Analyse des Organisations

This paper provides a historical chronology of economic activity in 16th- and 17th-century France that is based on wheat price series in Paris and Toulouse. A stochastic regime-switching model enables us to benchmark eras and summarize the salient features of a development difficult to appraise in all its complexity. A new class of Markov regime-switching time-series models is introduced to allow for nontrivial interdependencies between different types of cycles that make the economy grow at an unsteady rate. With a predominantly agricultural cycle, we uncover a strongly periodic Markov switching scheme for recorded wheat prices from the grain markets of Paris and Toulouse. Besides the periodic nature of the Markov chain, we also study whether a common factor determined the state of the economy in Paris and Toulouse or whether each series moved independently.

Keywords: Markov Regime-Switching Models, Historical Inflation Chronologies, Time-Series Model, Grain Prices

1. INTRODUCTION

Historians typically rely on documents from archives, chronologies of monarchies, major events such as wars, literature and other forms of art, and so on, to produce

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a synthesis of history. The chronologies extracted from such historical analysis are typically vague and imprecise. In this paper, we propose to use regime-switching models applied to two centuries of quarterly wheat price series recorded in the 16th and 17th centuries on the Paris and Toulouse grain markets to outline the salient features of a development difficult to appraise in all its complexity. Why wheat prices? Wheat was the commodity that fueled business activity like oil does today.[1] As the single most important commodity, its price followed very closely the ups and downs of the economy. We not only try to earmark eras of property and depression using univariate time-series regime-switching models, but we also attempt to analyze issues such as the interdependency of cycles in the two cities and the interdependency of seasonal and other components. To accomplish this we rely on a time-series stochastic regime-switching model introduced in a companion paper [Ghysels (2000)]. Besides univariate models, we also consider bivariate ones. Studying comovements of time series through multivariate regime-switching models has been of interest to empirical macroeconomists in determining the nature of the business cycle. See Diebold and Rudebusch (1994), Hamilton and Lin (1994), and Chauvet (1995), for example. The same questions raised in the business-cycle literature appear here in a historical context. Indeed, we want to find out whether, despite their geographic separation, cities such as Paris and Toulouse had a common single factor determining their ups and downs. Obviously, both had a strong common seasonal that affected the regime-switching scheme in both cities. However, is that enough to say that they were experiencing the same phases at the same time? We formally test this and find that both followed an independent path of regime switches. Of historical interest, of course, is also the comparison of chronologies for both cities and examination of their common features.

The paper is organized as follows: In Section 2, we provide a brief discussion of France in the 16th and 17th centuries, focusing on those elements relevant for the historical analysis of wheat prices in Paris and Toulouse. In Section 3, we cover the details of the time-series regime switch in models that we estimated. Both univariate and bivariate models are considered. We also discuss the chronologies provided by the time-series models and relate them to historical events. We provide conclusions in Section 4.

2. PROSPERITY AND DEPRESSION IN 16TH- AND 17TH-CENTURY FRANCE: A TALE OF TWO CITIES

Many historians have studied agricultural cycles during the so-called Modern period covering the three centuries from the 16th century until the French Revolution.[2] The prosperity of a nation depended critically on its ability to produce food, particularly grain, to sustain its workforce, army, tax base, and many other aspects of economic life. It is therefore no accident that economic historians paid considerable attention to grain prices, since they provide an indirect yet revealing measure of economic activity.[3] The study of wheat prices in France has been a fertile area of research because there are relatively well preserved and detailed records of market prices, the so-called *mercuriales*, for several regions of the country. We examine price series from two urban areas, namely, Paris and Toulouse. The series were collected by Frêche and Frêche (1967) for Toulouse and by Meuvret and Baulant (1960, 1962) for Paris.

It is a difficult task even to indicate the complexity of France in the 16th century, which is perhaps why the renowned French historian Fernand Braudel termed it the "long" 16th century. Literally hundreds of books were written on the economic, social, and political history of the country. It is absolutely impossible to summarize, for instance, the two volumes of Book I of *Histoire Economique et Sociale de la France—1450 à 1660* edited by Braudel and Labrousse (1970, 1977), or the two volumes by Duby and Mandrou (1968, 1984), *Histoire de la Civilisation Française*, or even more specifically the very detailed study on coinage in France by Spooner (1972) and the several chapters of Volumes III through V of the *New Cambridge Modern History*. It takes erudicity and particular skills to understand, interpret, and synthesize historical events produced by sources as diverse as archive documents, chronicles, political institutions, literature, arts, religious movements, and so on. It is surely not our ambition to match up to such endeavors that many famous historians undertook. First and foremost, we focus only on economic history. Second, we use exclusively time-series analysis.

We construct chronologies via regime-switching time-series models applied to wheat price series from the Paris and Toulouse grain markets and compare them with the turning points suggested by historical analysis. This comparison is reminiscent of that by Hamilton (1989), who focused on a single series, that is, U.S. GNP, to produce a chronology closely related to that published by the NBER, which is based on less formal methods somewhat similar to what historians try to do. Of course, for the 16th and 17th centuries, there are no precise NBER chronologies like that. The limited data sources, often incomplete and imprecise, that historians have to use result in rather vague and rough estimates of the beginning and end of different eras.[4]

The study of agricultural markets since the 16th century must be placed in the context of the transition from the feudal self-subsistent food sector to the market-oriented farm supplying grain to the ever-growing urban population of cities like Lyon, Marseilles, Nantes, Paris, and Toulouse. The 13th century propagated most of this evolution when French kings consolidated their power [Duby and Mandrou (1968, p. 191)], large trade fairs emerged (pp. 177–182) and cities took leading roles in economic activity and cultural events.

Indeed, the 13th century was mostly one of growth and prosperity. The French population is believed to have peaked at the end of the century at levels not seen again until the 18th century (Duby and Mandrou 1968, p. 173). It was also a century rich in intellectual developments; the establishment of the first Parisian university by Robert de Sorbon between 1192 and 1231 may serve as an example. The next two centuries were absolutely not carbon copies. The Hundred Years war, which lasted more than a century from 1337 until 1453, drained public finances and eroded some of the monarch's powers. Then there was the Black Pest, which took the lives of many citizens, particularly those who lived in confined places, like city dwellers. Economic activity picked up after the Hundred Years war but the recovery was not easy and took almost half a century, that is, until the beginning of the 16th century.

The structure of the agricultural sector is discussed in detail by Le Roy Ladurie (1977). The boundaries of villages and farmland remained roughly the same from the 13th until the 17th century and no major technological innovations took place during that period [Duby and Mandrou (1968, p. 130)]. France was a country of small farming with very few peasants owning their land. French nobility, who owned the land, preferred to live in cities, unlike the British landlords who remained on their property. Farmers divided their harvest into (1) rent payments, often in grain deliveries but sometimes in gold or silver coins; (2) so-called *dîmes* to the local abbey or clergy; (3) a tax imposed by the monarchy; and (4) the residual, left for sowing and own consumption or sale. Whereas the *dîmes* were levied as a fraction of the harvest (1 out of every 13 bushels, for instance), the other two dues were fixed amounts set prior to the harvest season. The landlords sold most of their grain deliveries on the local grain markets. The fact that farmers kept the residual was the cause of great hardships whenever crops were destroyed by bad weather, deliveries or harvesting were disrupted by war, and so on.

To conclude this section, a few words are offered about the data. The prices are quarterly and nominal and represent observations at the end of the quarter for one hectoliter of wheat.[5] Unfortunately, it was impossible to deflate the nominal prices because there are no regularly recorded price index series for the 16th and 17th centuries.[6] Hence, grain prices are expressed in *Livre Tournois*, the monetary unit of that era. The data are surely nonstationary, as Figure 1 shows. They cover a sample from 1520 to 1698. The series shown in Figure 2 do not start until 1521 because we reserve the first observations to condition initial values. We study the first differences of the log prices that appear in Figure 2. Because we do not have deflated data, we cannot disentangle price movements due to real and monetary factors. Some of the monetary movements could be partly recovered from the very detailed study by Spooner (1972) on coinage in France. The monetary system was quite complex, however, as different forms of currency, gold, silver, copper, and credit often did not meet the growing volume of transactions during both centuries. We do have some information on the influx of gold, for instance, which will be used to benchmark eras of nominal price increases as is discussed later.

A casual look at the series plotted in Figure 2 prompts several observations. First, the log first differences appear stationary. We discuss formal tests regarding stationarity shortly. It also appears from the three plots in Figure 2 that there are several extremely sharp price fluctuations in both markets, but the spurs and drops in each market do not seem to coincide. The lower part of Figure 2, which displays the spread, confirms this observation and also will be the subject of more formal testing.

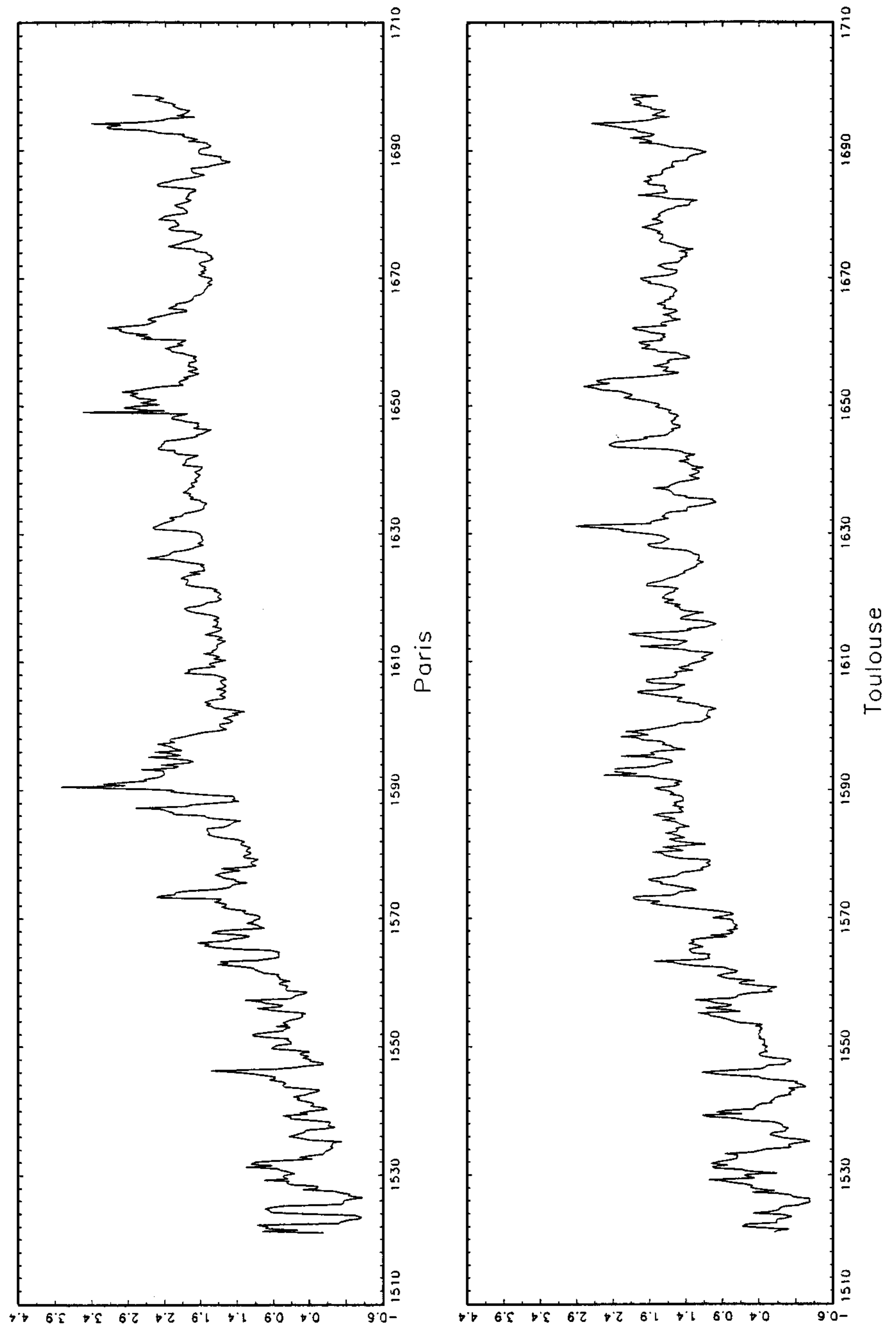

Figure 1. Log wheat prices in Toulouse and Paris (1521:1–1698:4).

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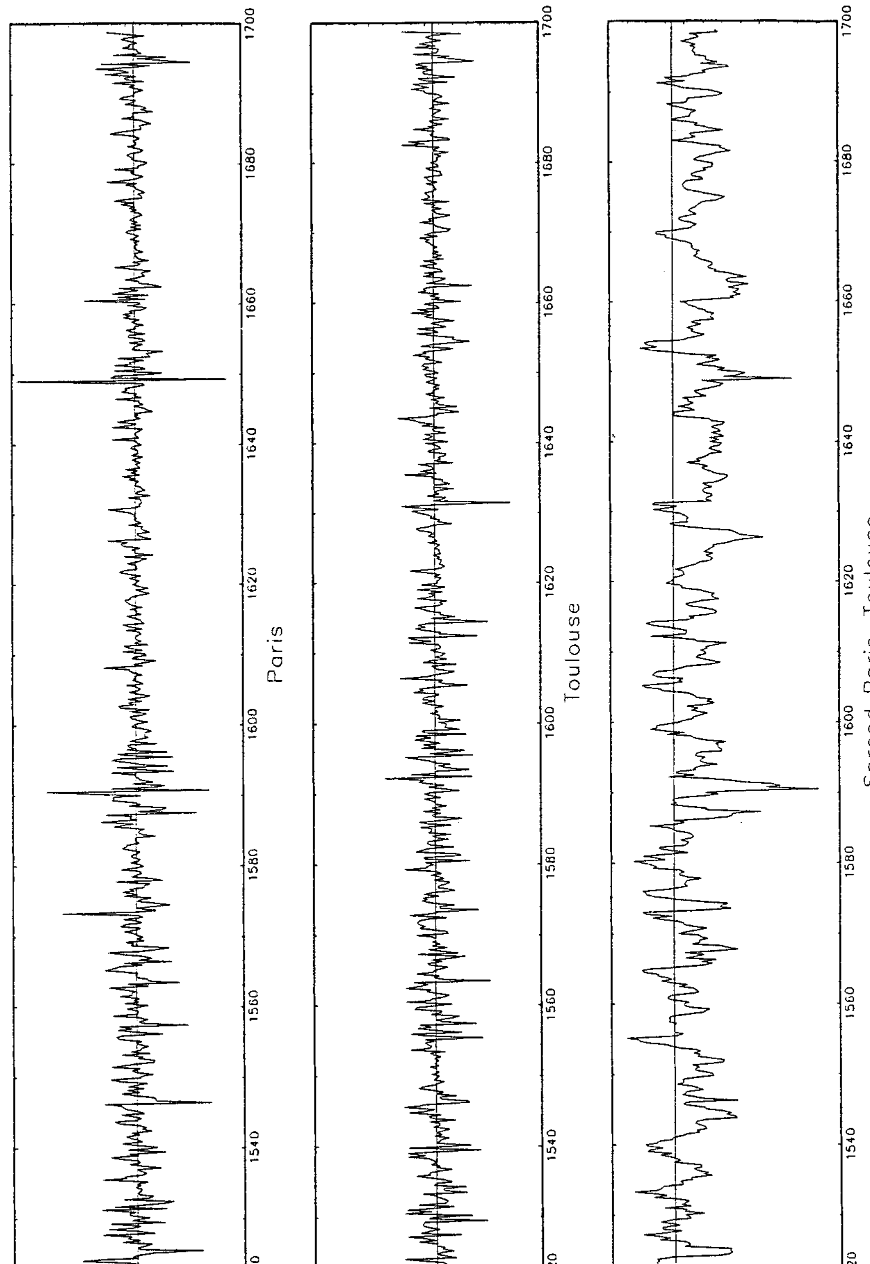

Figure 2. Log price changes in Paris and Toulouse and spread between markets (1521:2–1698:4).

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3. TIME-SERIES REGIME-SWITCHING MODELS

Section 3.1 presents the univariate time-series model estimation results. Section 3.2 is devoted to the extraction of chronologies. Finally, Section 3.3 covers bivariate models and examines factors common to both the Paris and Toulouse markets.

3.1. Univariate Time-Series Analysis

Before turning our attention to Markov switching models, we present some linear features of the data. Table 1 reports linear regression results for the $\Delta \log p_t$ series plotted in Figure 3. The summary statistics appearing at the bottom of the table show that prices tended to drop during the summer by an average of over 6% in Toulouse and roughly 1.35% in Paris. They increased more than 4% in Toulouse and almost 3% in Paris during autumn. The winter boosted prices in Toulouse by another 5% whereas prices in Paris were stable. Finally, during spring, prices in Toulouse fell slightly but remained stable in Paris. The first impression is that the Toulouse market seems to have greater seasonal fluctuations than the Paris market. A look at the ACF also shows stronger autocorrelations for Paris than for Toulouse. Also note that the residuals of the AR(8) model with seasonal dummies reported in the top panel of Table 1 still show considerable seasonality.[7] Indeed, regressing squared residuals on their own past reveals significant seasonality as well as significant lag effects.

Because we estimate periodic-regime switching models, we test whether periodicity appears in the linear representation reported in Table 1. Let us turn our attention to Table 2, where parameter estimates of a periodic AR(2) model and Wald tests for periodicity are reported.[8]

The results in Table 2 reveal that the third and fourth quarters in particular display a distinct pattern, if one relies on (robust) t statistics. The joint tests, reported at the bottom of the table, reenforce this finding. Again, the evidence for the Toulouse data is stronger than that for the Paris data. The plots in Figure 3 suggest that $\Delta \log p_t$ is stationary.[9]

We now turn our attention to Markov regime-switching models. Because the data are sampled at a quarterly frequency, we investigated the following model structure:

$$\Delta \log p_t = \mu[(i_t, \mathbf{s}_t)] + \sum_{j=1}^{4} b_j \{\Delta \log p_{t-j} - \mu[(i_{t-j}, \mathbf{s}_{t-j})]\} + \delta_t, \tag{1}$$

where $\delta_t \sim N[0, \sigma^2(i_t, \mathbf{s}_t)]$ with $\sigma^2(i_t, \mathbf{s}_t) = \sigma^2(i_t)\ \forall\, \mathbf{s}_t$ and

$$\mu[(i_t, \mathbf{s}_t)] = \alpha_0 + \alpha_1 i_t + \mathbf{1}_{\mathbf{s}_t} \alpha_s, \qquad s = 2, 3, 4, \alpha_1 > 0, \tag{2}$$

while the Markov chain is parameterized as

$$p(i_{t+1} = i \mid i_t = i, z_t) = \frac{\exp(z_t' \gamma_i)}{1 + \exp(z_t' \gamma_i)} \tag{3}$$

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Table 1. Linear regression models of log price changes

Paris market

$$\textit{Model}: \Delta \log(p_t) = \sum_{s=1}^{4} 1(s_t = s)\alpha_s + \sum_{j=1}^{8} \theta_j \Delta \log(p_{t-j}) + \varepsilon_t$$

α_1	0.6260	θ_1	−0.1323	θ_5	−0.1785
	(1.3007)		(0.0768)		(0.0431)
α_2	−0.2770	θ_2	0.0189	θ_6	−0.1464
	(1.3981)		(0.0298)		(0.0458)
α_3	−0.6847	θ_3	0.1006	θ_7	−0.0991
	(1.6395)		(0.0406)		(0.0378)
α_4	2.5412	θ_4	−0.0681	θ_8	−0.0161
	(1.1415)		(0.0405)		(0.0357)

$$\textit{Model}: \hat{\varepsilon}_t^2 = \sum_{s=1}^{4} 1(s_t = s)\tilde{\alpha}_s + \sum_{j=1}^{8} \tilde{\theta}_j \hat{\varepsilon}_{t-j}^2 + \mu_t$$

$\tilde{\alpha}_1$	195.7904	$\tilde{\theta}_1$	0.2929	$\tilde{\theta}_5$	0.0245
	(140.0948)		(0.0429)		(0.0088)
$\tilde{\alpha}_2$	287.8003	$\tilde{\theta}_2$	−0.0720	$\tilde{\theta}_6$	−0.0073
	(63.9180)		(0.0342)		(0.0118)
$\tilde{\alpha}_3$	428.6002	$\tilde{\theta}_3$	0.0339	$\tilde{\theta}_7$	−0.0079
	(100.6385)		(0.0155)		(0.0096)
$\tilde{\alpha}_4$	94.5657	$\tilde{\theta}_4$	−0.0230	$\tilde{\theta}_8$	−0.0114
	(31.8535)		(0.0108)		(0.0111)

Some descriptive statistics

Average price changes:		Q1: −0.0509	Q2: 0.0291	Q3: −1.3502	Q4: 2.860
ACF:	(1) −0.1072	(2) 0.0508	(3) 0.0638	(4) −0.0512	(5) −0.1779
	(6) −0.0957	(7) −0.0928	(8) −0.0235	(9) −0.0671	(10) −0.0180

Toulouse market

$$\textit{Model}: \Delta \log(p_t) = \sum_{s=1}^{4} 1(s_t = s)\alpha_s + \sum_{j=1}^{8} \theta_j \Delta \log(p_{t-j}) + \varepsilon_t$$

α_1	6.3924	θ_1	0.0188	θ_5	−0.0611
	(1.0125)		(0.0047)		(0.0350)
α_2	−2.1488	θ_2	0.0361	θ_6	−0.0638
	(1.2753)		(0.0393)		(0.0333)
α_3	−7.4921	θ_3	0.0922	θ_7	−0.0537
	(1.7448)		(0.0386)		(0.0364)
α_4	4.6903	θ_4	−0.2168	θ_8	−0.0340
	(1.0026)		(0.0434)		(0.0453)

Table 1. (Continued.)

$$Model: \hat{\varepsilon}_t^2 = \sum_{s=1}^{4} 1(s_t = s)\tilde{\alpha}_s + \sum_{j=1}^{8} \tilde{\theta}_j \hat{\varepsilon}_{t-j}^2 + \mu_t$$

$\tilde{\alpha}_1$	60.0191	$\tilde{\theta}_1$	0.0543	$\tilde{\theta}_5$	0.0402
	(25.5567)		(0.0386)		(0.0384)
$\tilde{\alpha}_2$	154.8692	$\tilde{\theta}_2$	0.0733	$\tilde{\theta}_6$	−0.0109
	(39.2765)		(0.0438)		(0.0221)
$\tilde{\alpha}_3$	498.9272	$\tilde{\theta}_3$	0.0749	$\tilde{\theta}_7$	0.0105
	(84.4534)		(0.0401)		(0.0188)
$\tilde{\alpha}_4$	78.8278	$\tilde{\theta}_4$	−0.0117	$\tilde{\theta}_8$	−0.0047
	(26.7928)		(0.0482)		(0.0430)

Some descriptive statistics

Average price changes:		Q1: 5.1432	Q2: −2.1871	Q3: −6.1682	Q4: 4.3556
ACF:	(1) 0.0270	(2) −0.0314	(3) 0.0757	(4) −0.1222	(5) −0.0690
	(6) −0.1383	(7) −0.0947	(8) 0.0600	(9) −0.0283	(10) −0.0514

Note: The standard errors were obtained via a HAC estimator with Bartlett window using (in RATS format) LAG = 4 and DAMP = 1.

with $i = 0$ or 1 and $\gamma_i(\cdot)$ is independent of $\mathbf{s}_t$. Equations (1) through (3) represent a special case of the general class of models considered in Ghysels (2000). Obviously, the choice of z_t will determine the nature of the Markov switching scheme. The original Hamilton model is obtained when z_t is constant through a reparameterization $p = \exp(\gamma_{10})/(1+\exp(\gamma_{10}))$ and $q = \exp(\gamma_{00})/(1+\exp(\gamma_{00}))$. A second specification for z_t involves a set of seasonal dummies, that is, a quarterly periodic stochastic regime-switching model. A third and final specification involves a stochastic transition probability matrix, namely, $z_t = (1, (\Delta \log p_t)^S)$, where $(\Delta \log p_t)^S$ is (an estimate of) the seasonal component of $\Delta \log p_t$. Hence, the transition probabilities are affected by the seasonal fluctuations in wheat price inflation. We will momentarily leave aside the specification of $(\Delta \log p_t)^S$ and simply note that (33) in this case becomes

$$p(i_{t+1} = i \mid i_t = i, z_t) = \frac{\exp\left(\gamma_{i0} + \gamma_{i1}(\Delta \log p_t)^S\right)}{1 + \exp\left(\gamma_{i0} + \gamma_{i1}(\Delta \log p_t)^S\right)}. \tag{4}$$

The seasonal component of $\Delta \log p_t$ affects the transition probabilities when $\gamma_{i1} \neq 0$ for either $i = 0$ or $i = 1$. Hence, the hypotheses of interest are $\gamma_{i1} = 0$ for either $i = 0$ and/or $i = 1$. Again, when $\gamma_{i1} = 0$ for both $i = 0$ and $i = 1$, we recover Hamilton's original model.

We first discuss the two specifications involving nonstochastic z_t. The model described by (1) and (2) implies that the discrete state variable i_t only affects the drift, not the seasonal dummies. Moreover, the fact that the Markov chain is periodic

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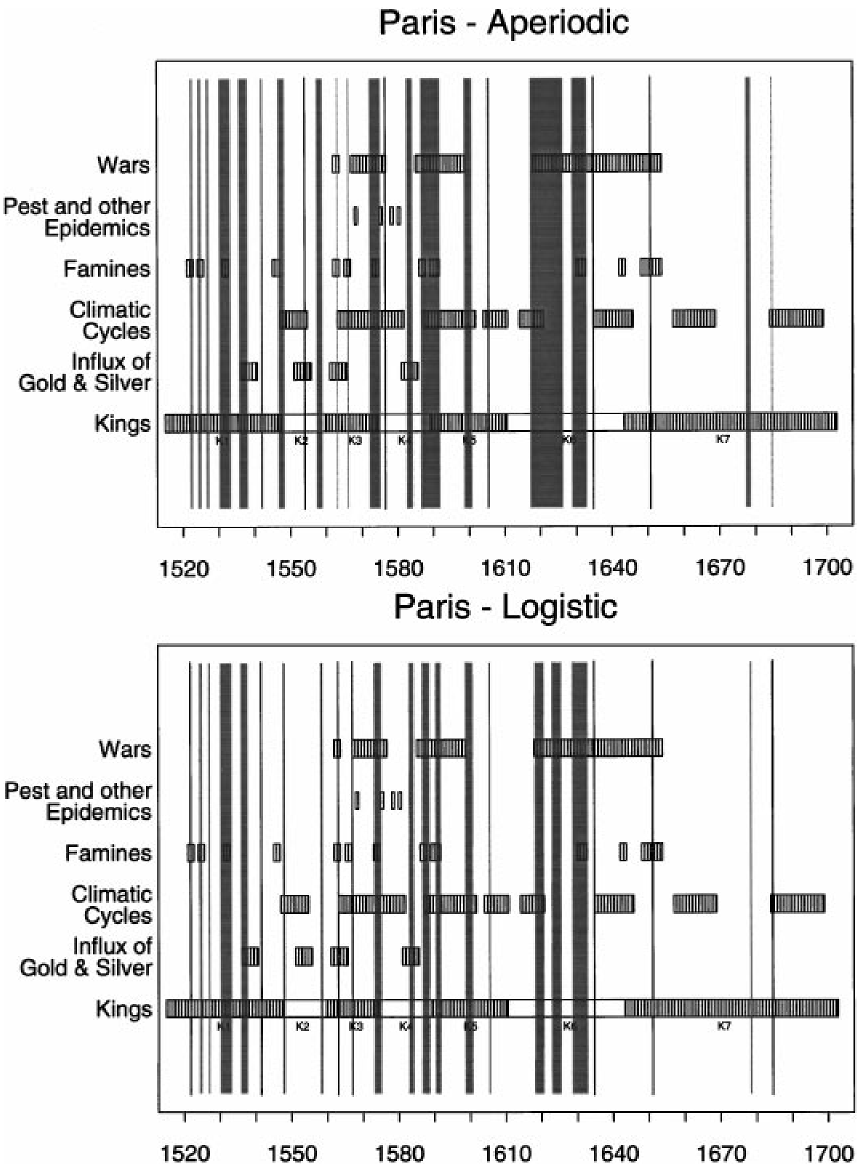

FIGURE 3. Aperiodic and logistic Markov switching chronologies.

and the innovation variance depends on i_t results in conditional heteroskedasticity with periodic features.[10]

The parameter estimates of the Markov regime-switching models appear in Table 3. We report three model specifications in Table 3 for the Paris and Toulouse markets. The first specification is "standard," that is, one in which the Markov

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Table 2. Linear periodic models of log price changes

$$\textit{Model}: \Delta \log(p_t) = \sum_{s=1}^{4} 1(s_t = s)\bar{\alpha}_s + \sum_{j=1}^{2} \bar{\theta}_{0j} \Delta \log(p_{t-j})$$
$$+ \sum_{j=1}^{2} \sum_{s=2}^{4} \bar{\theta}_{sj} 1(s_t = s) \Delta \log(p_{t-j}) + \eta_t$$

Paris market

$\bar{\alpha}_1$	0.3301	$\bar{\theta}_{01}$	−0.0828	$\bar{\theta}_{31}$	−0.1455
	(1.2046)		(0.0661)		(0.1594)
$\bar{\alpha}_2$	−0.9708	$\bar{\theta}_{02}$	0.1121	$\bar{\theta}_{32}$	−0.1319
	(1.4147)		(0.0381)		(0.1126)
$\bar{\alpha}_3$	−1.1824	$\bar{\theta}_{21}$	−0.1022	$\bar{\theta}_{41}$	0.0934
	(1.8324)		(0.2730)		(0.1082)
$\bar{\alpha}_4$	2.8771	$\bar{\theta}_{22}$	0.0782	$\bar{\theta}_{42}$	−0.2035
	(1.2166)		(0.0906)		(0.1141)

Joint Wald tests for periodicity, $H_0: \bar{\theta}_{s1} = \bar{\theta}_{s2} = 0$

$s = 2$: 0.86(0.35) $s = 3$: 1.70(0.19) $s = 4$: 7.03(0.01) $s = 2, 3, 4$: 10.81(0.01)

Toulouse market

$\bar{\alpha}_1$	4.6003	$\bar{\theta}_{01}$	0.2942	$\bar{\theta}_{31}$	−0.5483
	(0.8608)		(0.0724)		(0.1322)
$\bar{\alpha}_2$	−3.0663	$\bar{\theta}_{02}$	0.1135	$\bar{\theta}_{32}$	−0.7262
	(1.1794)		(0.0393)		(0.1947)
$\bar{\alpha}_3$	−3.5175	$\bar{\theta}_{21}$	−0.1162	$\bar{\theta}_{41}$	−0.1918
	(1.7890)		(0.1802)		(0.0848)
$\bar{\alpha}_4$	5.4040	$\bar{\theta}_{22}$	−0.1207	$\bar{\theta}_{42}$	0.0772
	(0.8734)		(0.1272)		(0.0622)

Joint Wald tests for periodicity, $H_0: \bar{\theta}_{s1} = \bar{\theta}_{s2} = 0$

$s = 2$: 0.65(0.42) $s = 3$: 5.03(0.03) $s = 4$: 5.89(0.02) $s = 2, 3, 4$: 12.03(0.01)

Note: For a description of standard errors and test statistic computations, see Table 1, where the sample is also described.

chain parameters are invariant through time. We denote this model specification as aperiodic. This model appears in the first columns of the two panels of Table 3. Next we report the model with a periodic Markov chain specification, where each p and q varies with $\mathbf{s}_t$, thus involving eight instead of two transition probabilities. Apart from the difference in the Markov chain structure, the two first models in Table 3 are alike because both specifications involve two drift parameters α_0 and α_1, two state-dependent variances σ_1 and σ_2, four polynomial lag parameters ϕ_1 through ϕ_4 as well as three seasonal dummies. The final model is the logistic model specified in equation (4).

Note that the differences between parameter estimates other than those pertaining to the Markov chain are statistically insignificant. The empirical estimates

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Table 3. Maximum likelihood estimates of aperiodic and periodic Markov regime-switching models

A. Paris market

	Aperiodic model		Periodic model	Logistic model	
	Estimates	Standard errors	Estimates	Estimates	Standard errors
State-dependent drift parameters					
α_0	−1.2799	0.8424	−1.4194	−1.2277	0.8520
α_1	1.7233	3.4735	1.7915	0.4376	4.1482
Autoregressive parameters					
ϕ_1	0.0505	0.0352	0.0694	0.0646	0.0322
ϕ_2	0.0473	0.0292	0.0453	0.0540	0.0303
ϕ_3	0.0440	0.0313	0.0578	0.0604	0.0268
ϕ_4	−0.0392	0.0300	−0.0348	−0.0637	0.0325
State-dependent standard errors					
σ_1	10.2073	0.5687	9.7190	10.9170	0.5346
σ_2	36.1085	2.7095	36.2535	39.3654	3.1829
Markov chain parameters					
p or γ_{10}	0.9306	0.0205	—	3.1286	0.4247
$p(1)$: Wi→Sp	—	—	0.8699	—	—
$p(2)$: Sp→Su	—	—	0.9078	—	—
$p(3)$: Su→Fa	—	—	0.9542	—	—
$p(4)$: Fa→Wi	—	—	0.9827	—	—
γ_{11}	—	—	—	−0.0712	0.0184
q or γ_{00}	0.7706	0.0643	—	0.8862	0.4317
$q(1)$: Wi→Sp	—	—	0.9277	—	—
$q(2)$: Sp→Su	—	—	0.9362	—	—
$q(3)$: Su→Fa	—	—	0.6561	—	—
$q(4)$: Fa→Wi	—	—	0.6680	—	—
γ_{01}	—	—	—	0.0224	0.0169
Seasonal dummies					
α_2	−0.9090	1.1113	−0.9854	−0.7432	1.1811
α_3	2.5244	1.2060	2.5031	3.0911	1.2028
α_4	2.8427	1.2039	2.9444	3.8410	1.1908
Log likelihood					
	−2296.8376		−2282.4341	−2288.7336	

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Table 3. (Continued.)

B. Toulouse market					
	Aperiodic model		Periodic model	Logistic model	
	Estimates	Standard errors	Estimates	Estimates	Standard errors
State-dependent drift parameters					
α_0	3.4538	0.9628	4.3074	4.6620	0.7949
α_1	6.3729	1.7974	6.0162	2.8907	2.6582
Autoregressive parameters					
ϕ_1	0.0542	0.0385	0.1025	0.0949	0.0307
ϕ_2	0.0823	0.0314	0.1168	0.0883	0.0306
ϕ_3	0.1143	0.0327	0.1269	0.1335	0.0298
ϕ_4	−0.1666	0.0346	−0.1092	−0.1609	0.0319
State-dependent standard errors					
σ_1	8.9263	0.6782	8.7712	10.1125	0.5489
σ_2	22.5436	1.7389	23.3575	25.7940	1.6399
Markov chain parameters					
p or γ_{10}	0.8489	0.0592	—	2.0486	0.4411
p(1):	—	—	0.8048	—	—
p(2):	—	—	0.6327	—	—
p(3):	—	—	0.9187	—	—
p(4):	—	—	0.9487	—	—
γ_{11}	—	—	—	−0.0965	0.0230
q or γ_{00}	0.7955	0.1081	—	−0.1332	0.6685
q(1):	—	—	0.8932	—	—
q(2):	—	—	0.9271	—	—
q(3):	—	—	0.6189	—	—
Su→Fa					
q(4):	—	—	0.5964	—	—
γ_{01}	—	—	—	0.2199	0.1630
Seasonal dummies					
α_2	−7.1556	1.0730	−6.9577	−6.6825	1.0068
α_3	−9.3930	1.1500	−10.1078	−7.5822	1.3781
α_4	−1.4083	1.0061	−1.0926	−0.9896	0.9247
Log likelihood					
	−2269.4073		−2233.0851	−2240.8897	

Notes: For details about sample see Table 1. Wi = Winter, Sp = Spring, Su = Summer, Fa = Fall.

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suggest that state 1 with $i_t = 0$ corresponds to relative price stability, that is, a low drift and a low variance, whereas state 2 with $i_t = 1$ has both a high drift and a high variance. For the Parisian market the low drift is, in fact, negative, whereas for the Toulouse market it is positive and relatively large. According to the α_0 and σ_0 estimated empirical results reported in Table 3, we finds that relative price stability means a steady-state inflation rate of about 3.5% (S.E. = 8.9%) for Toulouse and −1.3% (S.E. = 10.2%) for Paris. In contrast, with $i_t = 1$ $(\alpha_0 + \alpha_1)$, we have a steady-state inflation rate of 9.8% (S.E. = 22.5%) for Toulouse and 0.5% (S.E. = 36%) for Paris. The AR polynomial parameters reported in Table 3 show very little persistence of wheat price inflation within the two regimes; hence, the level shift in inflation appears to be the most important factor.

Let us consider now the Markov chain parameters appearing in Table 3. We observe that the inflationary state occupies a slightly larger proportion of the sample because $p > q$ for both series. As noted earlier, in Paris the inflationary state corresponds to relatively small growth with a very large variance, much larger than in Toulouse. When we consider the periodic version, we observe considerable variation in the switching probabilities throughout the year. Hence, the seasonal cycle strongly affects the transitions between the two states. In particular, it appears quite unlikely to leave the inflationary state except when spring and/or summer arrives, that is, when the harvest is known and market prices reflect anticipated shortages or abundances. Here again, the differences in switching probabilities $p(1)$ and $p(2)$ versus $p(3)$ and $p(4)$ are more pronounced for Toulouse. Likewise, the probability of moving toward the inflationary state is high during the summer and the fall because $q(3)$ and $q(4)$ are much lower than $q(1)$ and $q(2)$. One striking feature of the Markov chain parameter estimates is the appearance of near boundary estimates. This phenomenon is symptomatic of periodic Markov chain models and deserves some attention here.[11] However, it is worth noting that the LM test for periodicity [described by Ghysels (2000)] strongly rejects the aperiodic specification. Likewise, the LR test does so as well.[12]

Unconstrained periodic regime-switching models are, in many circumstances, overparameterized for the sample sizes typically encountered in economic time series. The results in Table 3 suggest that regime switches are still rare even with two centuries of data. Obviously, the evidence that, with approximately two centuries of data, one has in some sense, such a diversity of parameter estimates, quite strongly suggests periodicity. Yet, the presence of boundary parameters complicates the task of statistical hypothesis testing. In that regard, at least the LM test, involving the nonperiodic estimates away from the boundary is very useful. The LR test also supports the periodic model but the boundary estimates imply nonstandard conditions.[13]

The third and final model specification has transition probabilities determined by the logistic function (4), which does not involve the boundary-parameters issue potentially present in the periodic case. The specification of $(\Delta \log p_t)^S$ remains to be discussed, however. Estimating a seasonal component inevitably rests on a set of identifying assumptions to uncover the unobserved component. The model (1)–(4) is nonlinear and, in particular, has nonlinear seasonal effects. A priori, it is not obvious how to extract and/or formulate $(\Delta \log p_t)^S$ in a nonlinear framework. It also would be unnecessarily complicated to try to extract properly this component if it is only for the purpose of showing that seasonal fluctuations affect transition probabilities. We therefore restrict ourselves to a linear estimate of the seasonal, which is the fairly traditional method of extracting seasonal components. Some caution is necessary, however, because a procedure like the X-11 program involves *two-sided* filtering; that is, future as well as past $\Delta \log p_t$ are used to obtain an estimate of the seasonal component. Using future observations in z_t to model the Markovian regime-switching dynamics would not be appropriate. We therefore used one-sided linear filters, namely,

$$(\Delta \log p_t)^S = \frac{1}{k} \sum_{j=0}^{k-1} \Delta \log p_{t-4j},$$

which is a seasonal averaging filter over a span of k years. The last column of Table 3 reports the empirical estimates using a 4-year filter (i.e., $k = 4$). The coefficients of the autoregressive part, the mean shifts, and state-dependent variances are quite similar to those appearing in Panel A of the table, which covers the models with nonrandom transition matrices. Hence, we focus only on the parameters γ_{ij} of the logistic function (4). First, we note that the Wald test for the null $\gamma_{il} = 0$, is rejected at conventional significance levels for γ_{11} but not for γ_{01}. Note also that γ_{01} and γ_{11} have opposite signs. Hence, particularly during the summer, when prices typically drop, we should find opposite effects on switching probabilities, which is indeed the case if we examine, respectively, $q(3)$ and $p(3)$ relative to the estimates of p and q for the other quarters. We also note that the LR test for the null $\gamma_{i1} = 0$ strongly rejects this hypothesis, suggesting again a seasonal effect in transition probabilities.

3.2. Historical Analysis and Chronologies

In his original paper, Hamilton (1989) showed how a univariate stochastic regime-switching model for U.S. post-WWII real GNP growth almost exactly reproduced the NBER business-cycle chronology. Such chronologies are come from a committee at the Bureau involved in appraising and classifying the business-cycle patterns of the U.S. economy. As noted before, we do not have an equally detailed and researched chronology for the 16th and 17th centuries. Historians have been engaged in analyses similar to those of NBER dating committees, but with a more fragmented database. One of the best examples of historical business-cycle analysis for this period is that of Morineau (1977). His methodology is similar to that of Burns and Mitchell (1946), except that the descriptions of the subsequent stages of the business cycle are far less precise because of the lack of data. His analysis, and that of other historians, falls short of proposing an explicit set of dates. We do not expect to recover a business-cycle chronology because our series are wheat-price inflation series. For lack of any better series, however, they figure prominently in any attempt to study cycles. In fact, they also play a key role in Morineau's study. Using the smoothed probability estimates of the Markov switching models presented in the preceding section, we obtained chronologies of inflationary wheat-price states for 16th- and 17th-century Paris and Toulouse. Comparing those chronologies with the historical ones is the purpose of this section.

Figure 4 displays the chronologies extracted from the aperiodic Markov switching models for Paris and Toulouse (Table 3). The shaded vertical areas in Figure 4

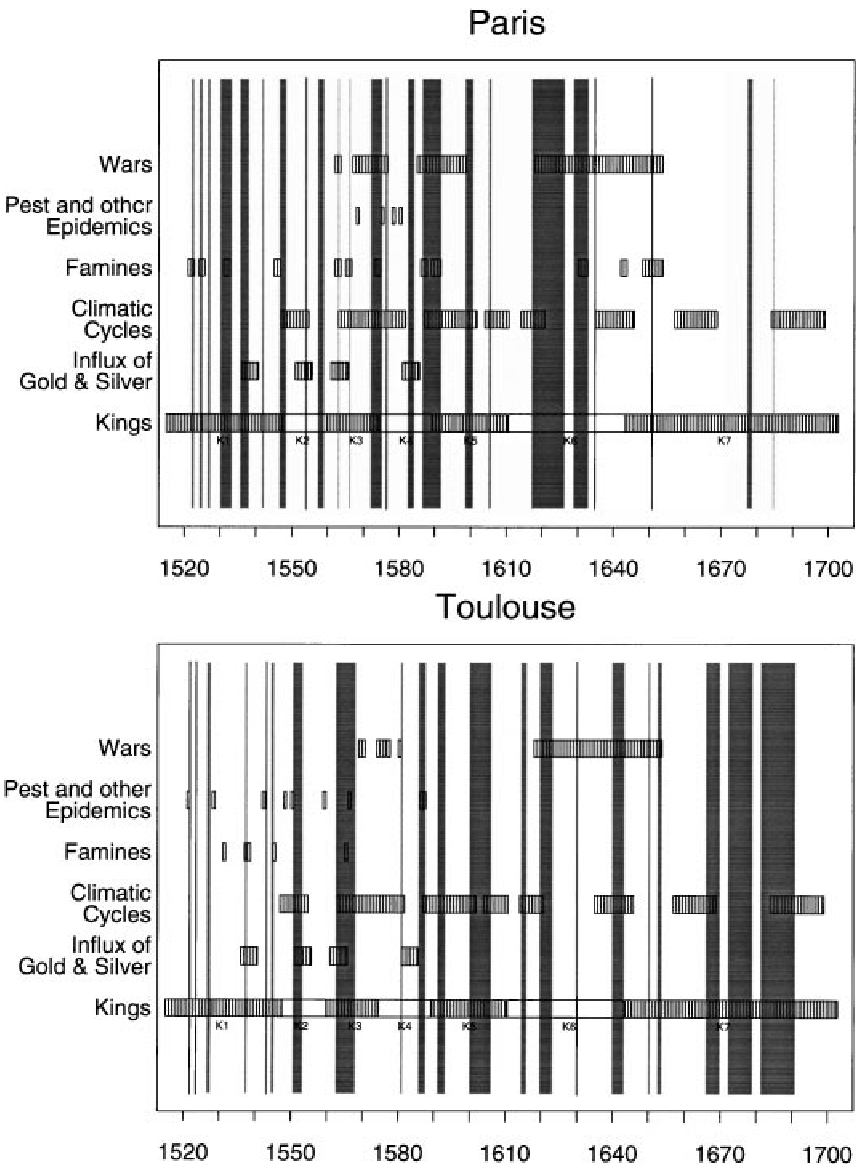

FIGURE 4. Markov switching (aperiodic) and historical chronologies.

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correspond to the smoothed probabilities for the inflationary states $i_t = 1$ exceeding 0.75. Superimposed on the shaded areas are a set of chronologies recovered from a number of historical studies. They cover political events such as wars and the reign of kings as well as economic, demographic, and climatological cycles, including the gold and silver influx from Spain, famines, and harsh winters. The superimposed historical chronologies are not exactly the same for Toulouse and Paris because certain factors, such as wars and famines, affected each city differently. In the Appendix, we provide a detailed account of the various sources of the historical chronologies. Consistent with the parameter estimates of p and q, we find that the inflationary state occupies a greater fraction of the sample, with an average duration of 19.96 quarters (though the median is only 12.5 quarters) versus a mean of 10.09 quarters (median = 6 quarters) for $i_t = 0$ for Paris and averages 20.23 (median = 19) versus 12.67 (median = 10) quarters, respectively, for Toulouse. Figure 4 shows that, for both Paris and Toulouse, the inflationary states appear to match up with episodes of famines, pests, and other epidemics but not so much with climatic cycles. In fact, famines, pests, and other epidemics do not match up very closely with the climatic cycles either. For Paris, war periods appear to match up more closely with the Markov chain chronology, at least during the 16th century. We also notice that the chronologies for Paris and Toulouse look quite different. Indeed, Paris experienced quite a few inflationary episodes, particularly during the 16th century, more so than Toulouse. During the 17th century, it is somewhat the reverse, particularly with a few long inflationary spells during the latter part of the century in Toulouse.

The statistical tests reported in Table 3 favored the periodic specification. Let us therefore consider chronologies obtained from the logistic Markov chain model appearing in the last column of each panel of Table 3. Figure 3 also displays the chronology for Paris obtained from the logistic model specification (the results for Toulouse are similar and thus are omitted here). We see some important differences, in particular, fewer regime switches, with the average length of the $i_t = 0$ state going from 6.73 quarters to 7.78 (yet the median remaining at 6 quarters). Although the mean duration increases, the inflationary states in the early 17th century appear to be much shorter. The matchup with famines, pests, and other epidemics appears the same. The lack of matchups with climatic cycles is again apparent.

3.3. Bivariate Regime-Switching Models

The univariate analysis in the preceding section suggests that Paris and Toulouse experienced different economic cycles. We investigate this issue now more formally by estimating a bivariate joint regime-switching model for the wheat price series of both cities together.

We noted in the introduction that multivariate regime-switching models have been used by Diebold and Rudebusch (1994), Hamilton and Lin (1994), and Chauvet (1995) to examine questions regarding the nature of business-cycle comovements among macroeconomic time series. One could describe this class

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as common-factor models with discrete states as discussed in detail by Ghysels (2000). So far, we have dealt only with the specific case described by equations (1) through (3). We now expand this by considering

$$\begin{pmatrix}\Delta \log p_t^P \\ \Delta \log p_t^T\end{pmatrix} = \begin{pmatrix}\mu_P\left[\left(i_t^P, \mathbf{s}_t\right)\right] \\ \mu_T\left[\left(i_t^T, \mathbf{s}_t\right)\right]\end{pmatrix} + \sum_{j=1}^{4} \tilde{b}_j \begin{pmatrix}\Delta \log p_{t-j}^P - \mu_P\left[\left(i_{t-j}^P, \mathbf{s}_{t-j}\right)\right] \\ \Delta \log p_{t-j}^T - \mu_T\left[\left(i_{t-j}^T, \mathbf{s}_{t-j}\right)\right]\end{pmatrix} + \begin{pmatrix}\delta_t^P \\ \delta_t^T\end{pmatrix} \quad \textbf{(5)}$$

where the superscripts P and T stand for Paris and Toulouse. The lag polynomial coefficient matrices $\tilde{b}_j$ are diagonal with elements b_j^P and b_j^T. Finally, as in (2), we have

$$\mu_h\left[\left(i_t^h, s_t\right)\right] = \alpha_o^h + \alpha_1^h\, i_t^h + 1_{st}\, \alpha_s^h \quad s = 2, 3, 4 \quad \alpha_1^h > o \quad h = P, T \qquad \textbf{(6)}$$

and δ_t^h are random Gaussian and dependent on i_t^h and $\mathbf{s}_t$ as in (1). The model has a common state variable if $i_t^P = i_t^T = i_t \; \forall\, t$, reducing the discrete state space from the bivariate (i_t^P, i_t^T) process to the degenerate (i_t, i_t). This implies that wheat price movements in both cities are driven by the same state process. For the Markov chain, without the common-factor restriction, we have the following transition matrix:

$$\begin{array}{cc|ccccc}
P & T & P & 0 & 0 & 1 & 1 \\
 & & T & 0 & 1 & 0 & 1 \\
\hline
0 & 0 & & P_{00}^{00}(s_t) & P_{00}^{01}(s_t) & P_{00}^{10}(s_t) & P_{00}^{11}(s_t) \\
0 & 1 & & P_{01}^{00}(s_t) & P_{01}^{01}(s_t) & P_{01}^{10}(s_t) & P_{01}^{11}(s_t) \\
1 & 0 & & P_{10}^{00}(s_t) & P_{10}^{01}(s_t) & P_{10}^{10}(s_t) & P_{10}^{11}(s_t) \\
1 & 1 & & P_{11}^{00}(s_t) & P_{11}^{01}(s_t) & P_{11}^{10}(s_t) & P_{11}^{11}(s_t)
\end{array}. \qquad \textbf{(7)}$$

Under the common restriction, both Paris and Toulouse share the same states. Therefore, transition matrix (7) reduces to a 2×2 matrix with transitions only between (0,0) and (1,1). Formally stated, this hypothesis can be written in terms of constraints on the transition matrix:

$$H_0\colon \quad P_{ij}^{kl}(s_t) = 0 \;\forall\; i, j, k, l \text{ s.t. } i \neq j \quad \text{or} \quad k \neq l, \qquad \textbf{(8)}$$

which reduces the 4×4 (possibly periodic) Markov chain to a 2×2 matrix. The hypothesis will be tested via a standard LR test.

The empirical results for the bivariate models with common-factor restrictions are reported in Table 4. Two versions of the model are reported: aperiodic and periodic. In each case we report the unconstrained bivariate model as well as the constrained one. The constraints corresponds to the null hypothesis of a common

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TABLE 4. Maximum likelihood estimates of aperiodic and periodic bivariate switching models

	Aperiodic unconstrained				Aperiodic constrained				Periodic unconstrained		Periodic constrained	
	Paris		Toulouse		Paris		Toulouse		Paris	Toulouse	Paris	Toulouse
	Estimates	Standard errors	Estimates	Standard errors	Estimates	Standard errors	Estimates	Standard errors	Estimates	Estimates	Estimates	Estimates
State-dependent drift parameters												
α_0	−1.2799	0.4581	3.4538	0.9368	−2.3295	1.0289	4.3851	1.1024	−1.4114	4.3034	−1.7023	4.7449
α_1	1.7237	0.3163	6.3726	1.7215	17.6787	3.7098	−12.9937	6.6307	1.7838	6.0198	1.6165	6.0770
Autoregressive parameters												
ϕ_1	0.0505	0.0331	0.0542	0.0330	0.0436	0.0385	0.0631	0.0424	0.0692	0.1024	0.0477	0.0774
ϕ_2	0.0473	0.0283	0.0823	0.0297	0.0269	0.0414	0.1270	0.0423	0.0454	0.1165	0.0454	0.1369
ϕ_3	0.0440	0.0280	0.1143	0.0299	0.0616	0.0335	0.1252	0.0440	0.0579	0.1268	0.0610	0.1463
ϕ_4	−0.0392	0.0287	−0.1666	0.0327	−0.0165	0.0313	−0.1645	0.0484	−0.0343	−0.1092	−0.0266	−0.1318
State-dependent standard errors												
σ_1	10.2071	0.5133	89263	6279	7.1876	0.5318	8.3316	0.5745	9.7318	8.7679	7.2756	8.0223
σ_2	36.1074	2.6150	225435	16641	7.7554	2.1958	27.34983	3.7176	36.2465	23.3478	32.5245	22.5961
Markov chain parameters												
p	0.9306	0.0185	0.8489	0.0544	0.9466	0.0210	←	—	—	—	—	—
$p(1)$	—	—	—	—	—	—	—	—	0.8695	0.8046	0.9841	←
$p(2)$	—	—	—	—	—	—	—	—	0.9234	0.8926	0.8966	←
$p(3)$	—	—	—	—	—	—	—	—	0.9079	0.6324	0.8424	←
$p(4)$	—	—	—	—	—	—	—	—	0.9326	0.9266	0.8991	←
q	0.7706	0.0609	0.7955	0.1021	0.5348	0.1310	←	—	—	—	—	—
$q(1)$	—	—	—	—	—	—	—	—	0.9535	0.9183	0.9871	←
$q(2)$	—	—	—	—	—	—	—	—	0.6550	0.6190	0.5949	←
$q(3)$	—	—	—	—	—	—	—	—	0.9815	0.9484	0.9929	←
$q(4)$	—	—	—	—	—	—	—	—	0.6655	0.5963	0.5984	←
Seasonal dummies												
α_2	−0.9089	0.3687	−7.1555	1.0631	−1.1831	1.3851	−6.8067	1.3919	−0.9809	−6.9582	−1.3369	−7.0254
α_3	2.5244	0.3552	−9.3929	1.1130	2.7111	1.4729	−6.6622	1.5096	2.5035	−10.1009	2.8397	−8.5978
α_4	2.8423	0.5659	−1.4081	1.0054	2.6170	1.4890	−1.2291	1.3025	2.9399	−1.0925	2.8665	−1.1690
Log likelihood												
	−4566.2449				−4611.6425				−4515.7057		−4610.5732	

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Markov chain specification appearing in (8). Because of space limitations we do not report the logistic model, but the results are essentially similar to those found with the periodic specification. A first clear indication that the common-factor restriction is not supported by the data is that the parameter estimates are very different and very imprecisely estimated. In particular, the parameter estimates of the Toulouse equations are quite implausible with large standard errors, especially the drift parameters. Also, $\hat{q}$ for this model is very low, at only 0.5348. The null hypothesis (8) is overwhelmingly rejected. For the periodic model the results are quite the same, though no standard errors are reported here for the reasons explained before.

4. CONCLUSIONS

This paper deals with the possibility of nontrivial interactions between cyclical variation and the repetitive intrayear dynamics of the economy. The presence or absence of such interactions is a fundamental issue. As in testing for cointegration, long memory, unit roots, or mean reversion, to name a few key issues, we are hampered by relatively short data sets—*only* 40 or 50 years of data for GNP. It is often said that it would be relatively easy to deal with this and many other issues in macroeconometrics if long spans of uniformly measured time series were available. The empirical example reported in Section 3 clearly shows that models this complex are still not identified sharply with a long historical record of wheat price movements over two centuries for two cities. Unfortunately, such data sets are still rare and have their own problems (e.g., differences in quality of measurements and no obvious deflators for nominal series). The parametric structures that we present in this paper lead to straightforward hypotheses that one can test regarding periodic features in stochastic regime switching. We show how significant the nontrivial interactions between cyclical variations and seasonal ones were in the 16th- and 17th-century economies. Of course, these economics were extremely primitive and rural in comparison to our modern economies, at least for the Western world. The models that we estimated generated chronologies, which we compared to the fragmented and imprecise chronologies constructed by historians from incomplete and partial data sets. We found that the economic cycles in Paris and Toulouse were unrelated and driven by different factors. Though both cities were governed by the same king, their inhabitants experienced very different lives. The analysis in this paper provides a time-series-analysis alternative to standard historical chronologies. The method that we propose is easily extended to other types of time series.

NOTES

1. See, for instance, Meuvret (1971), Morineau (1977), and Spooner (1968) for detailed discussions of the economic history of 16th- and 17th-century Europe and, in particular, the role of wheat.
2. See, for instance, Meuvret and Baulant (1960), Braudel and Labrousse (1970, 1977), Meuvret (1971), Saint-Amour (1988, 1991), and Chevet and Saint-Amour (1991).

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3. The historical studies best known to economists are those of the British economist and statistician, William H. Beveridge, who collected *annual* wheat price data over four centuries. It led also to several discussions regarding the use of periodogram analysis and its interpretation; see, for instance, Granger and Elliott (1967). In our study, we use hitherto unexplored *quarterly* time series, which will be discussed later.

4. The best example is the chapter by Morineau (1977) on business cycles in Braudel and Labrousse (1977). Unfortunately, Morineau did not produce an explicit chronology; his analysis remained descriptive and was accompanied by some time-series plots, notably of wheat prices. For further discussion, see Section 3.3.

5. Unlike today, there was no government-imposed quality standard on quoted grain prices or agricultural products in general. Hence, we can only guess how the quality of 1 hectoliter of grain varied through the sample.

6. Some calculations of general price movements exist [see for instance Spooner (1968, Table 1)], but they are very imprecise and are calculated at 15-year or greater time intervals. To give some idea of the imprecision, a price index 1471–1472 = 100 takes values ranging from 78.8 to 126.9 in 1487–1514 and 4.77 to 627.5 in 1590–1598 depending on the method of calculation.

7. We considered higher-order lags but did not find any significant parameters beyond the eighth lag, which is why we focus on the AR(8) model.

8. From the discussion in Ghysels (2000, Sect. 2), we know that a periodic AR(2) structure corresponds to a complicated seasonal ARMA model. Hence, the fact that only two lags were taken in the periodic model is not in contradiction to the AR(8) specification appearing in Table 1. Moreover, higher-order periodic models yielded results similar to those reported in Table 2.

9. Standard Dickey–Fuller tests do not reject the $I(1)$ specification but do reject $I(2)$. Because of the periodic structure, one may test the null hypotheses of $I(1)$ and $I(2)$ with tests appropriately designed for these types of models. Such tests are discussed by Ghysels et al. (1996). We do not report the results here because they also overwhelming endorsed the $I(1)$ specification.

10. The evidence reported in Table 1 appears to support the presence of such effects because of the seasonal variation in the variance.

11. The occurrence of boundary parameter estimates in Hamilton-type models is not uncommon, even in aperiodic models. For instance, Cecchetti and Lam (1992) estimated regime-switching models using annual output data from nine OECD countries and reported boundary parameter estimates for four countries. Phillips (1991), also using international data, reported similar results.

12. We did report standard errors for the parameter estimates of the periodic models in Table 3. If the underlying parameters are at the boundary, then standard regularity conditions do not hold. If they are not at the boundary, then standard errors can be computed the usual way. The information in the sample about the parameters, despite the length of the sample, is so limited that the Hessian is nearly singular, suggesting identification problems so that standard errors are enormous or are impossible to calculate numerically. In all of our computations, we used GAUSS code. In particular, we used the Maxlik and HESS procedures to obtain the ML estimates.

13. One could consider estimators with smoothing properties yielding nonboundary estimates. Bayesian estimators, of either the type proposed by Hamilton (1991) or the type proposed by Albert and Chib (1993) and McCulloch and Tsay (1994) involving the Gibbs sampler, are two such examples. However, with two centuries of data, it is clear that boundary estimates are not so much a small-sample phenomenon. Therefore, it is somewhat artificial to force estimates away from the boundary.

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APPENDIX: SOURCES OF HISTORICAL CHRONOLOGIES

In this Appendix we document the sources of the historical chronologies superimposed on the smoothed Markov switching probability chronologies appearing in Figures 3 and 4. Morineau (1977) was our principal source of information, complemented by data from Duby and Mandrou (1984) as well as correspondence with the French historian Jean-Michel Chevet (INRA, Paris). The "Pest and other Epidemics" chronology for Paris is reported by Morineau (1977, p. 907) as 1568, 1575, 1578, and 1580. For Toulouse, Morineau (1977, p. 906) reports 1521, 1528, 1542, 1548, 1550, 1559, 1566, and 1586–1587. The "Famine" chronology, referred to in the literature as *disette et famines* for the Paris region is reported by Morineau (1977, p. 944) as 1521–1522, 1524–1525, 1531–1532, 1545–1546, 1562–1563, 1565–1566, 1573–1574, 1586–1587, 1589–1591, 1630–1632, 1642–1643, 1648–1653. For the Toulouse region the dates are 1531, 1537–1538, 1545, and 1565 [see Morineau (1977, p. 906)].

Several studies have examined climatic cycles; see, for instance Slicher van Bath (1963). There appeared to be several cold weather spells over the following periods: 1547–1554, 1563–1581, 1587–1601, 1604–1610, 1614–1620, 1635–1645, 1657–1668, 1684–1699 [see also Morineau (1977, p. 955)]. The next chronology refers to the influx of gold and silver from the American continent through Spanish expeditions. The monetary movements during the 16th century are quite complex; for example, the Spanish monarchy declared bankruptcy twice. A very detailed study regarding the French money supply and the influences of Spanish gold and silver is provided by Spooner (1972). The "Influence of Gold and Silver" chronology only provides the peak periods, which are benchmarked by Morineau (1977, p. 958) as 1536–1540, 1551–1555, 1561–1565, and 1581–1585.

The "War" chronology is based on three major conflicts that were waged throughout the 16th and 17th centuries: (1) the religious wars (guerres de religion), (2) the Thirty Years' war, and (3) the so-called *Fronde*. The religious wars were spread over several mutually overlapping conflicts that dragged on several years. They were for the Paris region: (a) invasion of Rouen and Battle of Dreux, 1562–1563, (b) various wars from 1567 to 1598 with a siege of Paris (1569–1570), massacre of Saint Barth (1574–1576), and a second siege of Paris (1585–1598). For the Toulouse region, they were (a) various wars from 1569 to 1570 and from 1574 to 1577, including agitation in the south (1575–1576), the Saint Barth

TABLE A-1. Kings and their reigns

King	Symbols	Reign
François I	K1	1515–1547
Henri II	K2	1547–1559
Charles IX	K3	1560–1574
Henri III	K4	1574–1589
Henri IV	K5	1589–1610
Louis XIII	K6	1610–1643
Louis XIV	K7	1643–1715

massacre (1574–1576), in addition to the war in the Cahors region (1580). The Thirty Years' war took place in Germany from 1618 to 1648, and ended with the Peace of Westphalia; it involved French interventions, notably led by Richelieu, minister to Louis XIII. It was immediately followed by the *Fronde*, a collection of conflicts from 1648 to 1653. The dates for this chronology were constructed from several sources [notably, Duby and Mandrou (1984)] and with the help of historian Jean-Michel Chevet (INRA, Paris).

Table A-1 provides the reigns of French kings and their corresponding symbolic reference in the chronology.