Stat Methods Appl (2009) 18:67–86
DOI 10.1007/s10260-007-0075-3

ORIGINAL ARTICLE

Regime switching: Italian financial markets over a century

Margherita Velucchi

Accepted: 16 October 2007 / Published online: 14 November 2007

Abstract The frequency of crashes and the magnitude of crises in international financial markets are growing more severe over time. Recent financial crises are not singular events portrayed in recent accounts, rather, they erupt in circumstances that are very similar to the economic and financial environments of the earlier eras. This paper analyzes the Italian stock market in two very peculiar periods (1901–1911 and 1993–2004): the "Second" and the "Third industrial revolution". We use Markov Switching Models to test whether the Italian stock market volatility has increased in the long run and whether it can be represented by different regimes. We find that volatility regimes exist; that Banking sector has a central role and "New economy" sectors perform quite well while traditional sectors do not, in both periods.

1 Introduction

Economists often compare financial crises developed in different contexts to investigate whether the crises are growing more frequent and more severe over time (Delargy and Goodhart 1999; Eichengreen and Bordo 2004; Bordo and Murshid 2001; Bordo et al. 2001). The comparison of crises in economic, institutional, geographic and, especially, historical different contexts may seems to be bold, but the evidence that "history matters" is definitely not new to economics. Indeed, many authors suggest

I am grateful to comments from Giampiero M. Gallo, Christian T. Brownlees, Marco J. Lombardi, Renato Giannetti and from participants in the 2005 S.Co. Conference in Bressanone, especially the discussant Francesco Lisi. Thanks are also due to two anonymous referees that strongly helped improve the overall structure and readability of the paper.

M. Velucchi (✉)
Dipartimento di Statistica "G. Parenti", Università di Firenze,
Via G. B. Morgagni, 59-50134 Florence, Italy
e-mail: velucchi@ds.unifi.it

to focus on the comparison between pre-1914 crises and 1990s crises showing that some of the "peculiarities" of modern financial markets resemble what happened just a century ago (Delargy and Goodhart 1999; Eichengreen and Bordo 2004). Wilson et al. (1990) stress the relationship between increased volatility, panics and crashes testing whether, in the long run, increased volatility precedes, coincides with or follows crises; Bordo (1986) analyzes comparatively the relationships between crises, stock market behavior and the money supply; Delargy and Goodhart (1999), Bordo and Eichengreen (2004), Bordo and Murshid (2001), Bordo et al. (2001), focus on financial markets behavior in the long run, suggesting a comparison of financial crises to test whether the frequency of crashes and the magnitude of crises are growing more severe over time. In particular, Delargy and Goodhart (1999) compare the Asian financial crisis in 1997 with late nineteenth century crises. They find that the economic and financial environments of the two eras are very similar claiming that the Asian crisis had its roots in private sector over-expansion as it happened in the pre-1914 crises.[1] Eichengreen and Bordo (2004) compare the Argentina-Barings crisis of 1890 with the 1990s crises. They partially confute Delargy and Goodhart (1999) showing that crises are more frequent today but not more severe and that losses and recovery from such crises were not faster before 1914.

According to this literature, we propose a long run analysis of Italian stock market in two very peculiar periods (1901–1911 and 1993–2004): the "Second" and the "Third industrial revolution" in Italy. Indeed, these periods are both characterized by strong changes in the structure of the economy due to important technological innovations (electricity and information technology, respectively) and by a large expansion of the stock market.

We use volatility modelling to study the Italian financial markets over a century, to investigate whether there has been an increase in volatility and whether relationships between innovative and traditional sectors can be identified. Volatility modelling literature has been flourishing since the seminal papers on ARCH (Engle 1982) and GARCH (Bollerslev 1986) have been published. Since then an impressive number of generalizations have been suggested (Nelson 1991, Rabemananjara and Zakoïan 1993; Glosten et al. 1993; Zakoïan 1994; Engle and Kroner 1995; Ballie et al. 1996) to take into account asymmetries of the series and to provide a systematic comparison of volatility models. A different strand of literature, maintaining the time-varying volatility assumption of GARCH models, is represented by the Markov Switching approach (Hamilton 1989, 1994; Hamilton and Susmel 1994). Markov Switching models, modelling the series as a mixture of regimes (high and low returns and/or volatility periods), turn out to be particularly interesting to compare financial markets over the long run. In this approach, parameters are viewed as the outcome of a discrete-state Markov process and they are known to accurately capture typical stock market patterns such as jumps and crashes (Billio and Pelizzon 2000; Kuo and Lu 2005; Mills and Wang 2003; Gallo and Otranto 2007).

[1] They analyze real demand, external relationships and domestic financial conditions in USA (1873, 1890–1891, 1893, 1907), Italy (1893, 1907), Austria (1873), Australia (1893), Argentina (1873) in the late nineteenth and early twentieth century comparing them to the economic environment of the Asian Tigers of the 1990s.

In this paper, we use a Markov Switching approach to analyze stock market volatility in Italy in two periods: the first decade (1901–1911) and the last decade (1993–2004) of twentieth century. We use an univariate 2-state Markov Switching Model to analyze the behavior of the market, then we investigate the roots of the increased volatility focusing on sector indices. We expect to find evidence of high and low volatility regimes and identify the "leading sectors", in terms of under/over performing sectors with respect to the market performance. Then, a Multivariate extension of the 2-state Markov Switching Model is used to stress the existence of relationships between the sectors and whether these relationships changed over time.

This paper is structured as follows: a brief description of the economy and of the stock market evolution in both periods is given in Sect. 2, the model is introduced in Sect. 3, Sect. 4 describes the data and Sect. 5 discusses the results. Section 6 concludes.

2 A saecular overview on Italian economy

According to many scholars, recent international financial crises are not events developed in new account; rather, they resemble old financial crises, especially the pre-1914 crises (Delargy and Goodhart 1999; Eichengreen and Bordo 2004). Recent financial crises erupted in circumstances that are very similar to the economic and financial environments of the former era, at least in some important features. This section sketches the main aspects of the Italian economy in the first and the last decade of the twentieth century to stress the analogies over the century.

2.1 The first decade: 1901–1911

At the end of nineteenth century, Italy has not completed the *industrialization process* and its economic development is still behind the most industrialized countries (Castronovo 1995). Notwithstanding, during the first decade of the twentieth century, Italy reaches the most advanced countries: between 1897 and 1907, the GDP rate of growth (compound average) is 2.5%, the average annual industrial production rate of growth is 5.5% and the average fixed investment rate of growth is 10.5% (Cotula and Garofalo 1996). This decade is also characterized by the introduction of some important technological innovations and development of new sectors. Telegraph in 1894, for example, increases enormously the speed of financial transactions, favoring the integration of local stock markets (especially Milano and Genova) and the expansion of Borsa di Milano, while the introduction of electricity and new chemical products (like fertilizers, dye stuff and explosives) help the emerging of the new capital intensive firms obtain adequate funds by the financial system. This period is commonly known as the *Italian industrial revolution*. Between 1895 and 1907, the good performance of economic indicators is accompanied by a large stock market boom. The number of quoted firms at Borsa di Milano increases from 30 to 171 (Table 1), showing a peak of 45 new entrants in 1905 (Siciliano 2001). This is not simply an increase in number of quoted firms, because they are qualitatively very important for the Italian economy (De Luca 2002). The largest Italian firms are quoted at Borsa di Milano and all the sectors characterizing the "New" and the "Old economy" are represented. In 1903, 72% of the Italian share capital is quoted and almost all the increases in capital are realized by stock market new emissions (Siciliano 2001; Baia Curioni 2000). However, although the early twentieth century shows a very positive trend of the Italian economy, in 1907 one of the worse financial crises of its history takes place.[2] Table 2 shows that returns are constantly increasing up to 1905, then a downturn behavior starts changing completely the Italian financial system: from a well developed mix of *market-oriented* and *bank-oriented* system to a pure *bank-oriented* system that lasted until 1980s (Baia Curioni 1995; Bonelli 1971; Confalonieri 1982; La Francesca 2004).

2.2 The last decade: 1993–2004

The Italian economic structure of the last decade 1993–2004 is characterized by strong institutional changes (the role of Europe and the introduction of euro) and by the privatization policy of the late nineties. The "globalization" phenomenon and the information technology sectors ("New economy" sectors) role represent a deep structural change of the economy, whose effects are often compared to those of the Second Industrial Revolution. Indeed, many high tech and capital intensive firms are quoted during the late nineties.

The decade is also characterized by frequent and successive waves of international financial crises involving several stock markets: the 1992 collapse of Europe's fixed parities, the 1994 collapse of the Mexican peso, the 1997–1998 East Asian crisis, Russia, Brazil and the September 11 terroristic attack in 2001 (De Long 2001).

The economic growth of the last decade is not as high (on average) as that of the first decade of the century but, focusing on the stock market the period between the beginning of 1999 and the end of 2000 shows growth rates that resemble the 1905–1907 boom. During the last decade, Borsa di Milano experiences particularly high returns between 1996 and 2000, almost doubling the European average (Table 2). Since 1998, the number of firms quoted at Borsa di Milano increase after a decade of negative trend (Table 2): more than 50% of the new firms quoted are small and young (De Luca 2002). High returns persist until the autumn of 2000. Since that, international stock markets start suffering losses that reduce substantially the gains obtained during the previous years. The Mib30 annual return is +5.4% in 2000 and −25.1 and −23.7% in 2001 and 2002, while it appears to be positive after 2002 (+14.9 and +17.4% in 2003 and 2004, respectively).

3 The model

The Hamilton's seminal paper in 1989 suggested Markov switching techniques as a method for modelling time series. In the Hamilton approach, the parameters are viewed as the outcome of a latent discrete-state Markov process based on the fact that variables

[2] Siciliano (2001) shows that the boom before the 1907 stock market crisis has been the largest of the century and that the loss after the crash has never been completely re-absorbed by the Italian stock market. Between 1905 and 1907, Italian stock market loses 80% of its value: if we compare the market index price over a century starting with 1905 (=100), the value at 2000 is around 15.

Table 1 Number of quoted firms in Italy

Year	Quoted firms
(1897–1911)	
1897	30
1898	33
1899	46
1900	59
1901	60
1902	70
1903	72
1904	91
1905	134
1906	148
1907	171
1908	169
1909	168
1910	157
1911	159
(1993–2004)	
1993	259
1994	260
1995	254
1996	248
1997	239
1998	243
1999	270
2000	297
2001	294
2002	295
2003	279
2004	278

can be subject to occasional, discrete shifts in mean and/or variance. This approach has been widely used to describe and forecast financial time series (Rockinger 1994; Van Norden and Schaller 1997) while several others contributions and extensions of the original Hamilton's model have been developed and applied to different fields of the economic activity showing its high flexibility and forecast ability (Billio and Pelizzon 1997, 2000; Khabie-Zeitoun et al. 1999; Jeanne and Masson 2000; Kuo and Lu 2005; Mills and Wang 2003; Gallo and Otranto 2007).

In a financial context, regime-switching models refer to a situation in which stock market returns (and/or volatility) are drawn from two different distributions, where known stochastic processes determine the likelihood that each return (and/or volatility) is drawn from a given distribution.

Table 2 Indices returns

Year	Returns
I70 Returns	
1901	+3.7%
1902	+7%
1903	+15.7%
1904	+13.7%
1905	+7.7%
1906	−9.7%
1907	−11.6%
1908	−13.7%
1909	−1.5%
1910	+0.9%
1911	−4.8%
Mib30 Returns	
1993	+37.4%
1994	+3.3%
1995	−6.9%
1996	+13.1%
1997	+58.2%
1998	+41%
1999	+22.3%
2000	+5.4%
2001	−25.1%
2002	−23.7%
2003	+14.9 %
2004	+17.4 %

Consider a random variable s_t that can assume only integer values $\{0, 1, \ldots, N\}$. Suppose that the probability that s_t equals some particular value j depends on the past only through its most recent value s_{t-1}:

$$P\{s_t = j\,|s_{t-1} = i, s_{t-2} = k, \ldots\} = P\{s_t = j\,|s_{t-1} = i\} = P_{ij}. \tag{1}$$

This process is described as a N-state Markov Chain with transition probabilities $\{p_{ij}\}_{i,j:0,1,2,\ldots,N}$. The transition probability gives the probability that state i will be followed by state j.[3]

A two state Markov Switching Model for r_t, can be represented as follows:

$$r_t = \begin{cases} \mu_0 + \sigma_0\epsilon_t, & \textit{if } s_t = 0 \\ \mu_1 + \sigma_1\epsilon_t, & \textit{if } s_t = 1 \end{cases} \tag{2}$$

where $\varepsilon_t \sim i.i.d.N(0, \nu^2)$ and $s_t = \begin{cases} 0 \textit{ if return and/or volatility is low} \\ 1 \textit{ if return and/or volatility is high} \end{cases}$

Let s_t be a two states Markov Chain and define the transition probability matrix as $\mathbf{P} = \{P_{i,j}\}$:

[3] Note that $p_{i1} + p_{i2} + \cdots + p_{iN} = 1$.

$P(s_t = 0|s_{t-1} = 0) = P_{00},$
$P(s_t = 1|s_{t-1} = 0) = P_{01} = 1 - P_{00},$
$P(s_t = 1|s_{t-1} = 1) = P_{11},$
$P(s_t = 0|s_{t-1} = 1) = P_{10} = 1 - P_{11}.$

A related question is when the turning point is likely to occur. Therefore, it is useful to know the average *duration h* of the states (regimes):

$$E(h_i) = \frac{1}{P_{ij}}, \quad i, j : 0, 1, \quad i \neq j \tag{3}$$

In a multivariate context,

$$R_t = \begin{cases} v_0 + B_0 u_0, & \text{if} \quad s_t = 0 \\ v_1 + B_1 u_1, & \text{if} \quad s_t = 1 \end{cases} \tag{4}$$

where R_t is the (n x 1) vector of the endogenous variables, v_0 and v_1 are the (n x 1) vectors of intercepts in state 0 and 1, respectively, B_0 and B_1 are the (n x n) structural matrices[4] in state 0 and 1, respectively while u_0 and u_1 are the errors in state 0 and 1, respectively, distributed as $N(0, \Omega_\mathbf{s})$.[5] When the process is in state 0, the observed vector R_t is assumed to be drawn from a $N(\mu_\mathbf{0}, \Omega_\mathbf{0})$ while when the process is in state 1, then it is assumed to be drawn from a $N(\mu_\mathbf{1}, \Omega_\mathbf{1})$. The parameter vector is given by $\theta = (\mu_\mathbf{0}, \mu_\mathbf{1}, \Omega_\mathbf{0}, \Omega_\mathbf{1}, \mathbf{p_{00}}, \mathbf{p_{11}})$. In a n-dimensional two states Markov Switching Model the number of switching parameters is equal to $\Phi = \mathbf{n} + \mathbf{n}(\mathbf{n}+\mathbf{1})/\mathbf{2}$ and $\theta = 2\Phi$.

Smoothed inference can be calculated using the Expectation Maximization algorithm (Hamilton 1989; Kim 1993), designed for a general class of models where the observed time series depend on some unobservable stochastic processes. In a Markov Switching approach, these are the regime variables s_t.

4 The data

We use the daily price series of seven sectors indices for the first decade of twentieth century (Fig. 1) and the daily price series of ten sectors indices for the last one (Fig. 2); the sectors composition do not change much during a century but some new sectors are introduced. Data consist of 3,164 observations for the first period (January, 2, 1901 to December, 29, 1911) and 3,071 observations for the last period (January, 2, 1993 to February, 28, 2004), respectively. We also consider Index 70 and Mib30 to proxy the market behavior in both periods; these indices are calculated on the 70 and 30 most capitalized firms of the stock market, respectively.[6] The daily returns are calculated as the change in the logarithm of the closing prices of two successive days. Financial

[4] These matrices describe the relationship between endogenous variables within each regime.

[5] Ω is the variance-covariance matrix in state $s = (0, 1)$.

[6] The I70 index collects historical data since January, 1888 (Baia Curioni 2000). The Mib 30 historical index is provided by Borsa Italiana (www.borsaitalia.it).

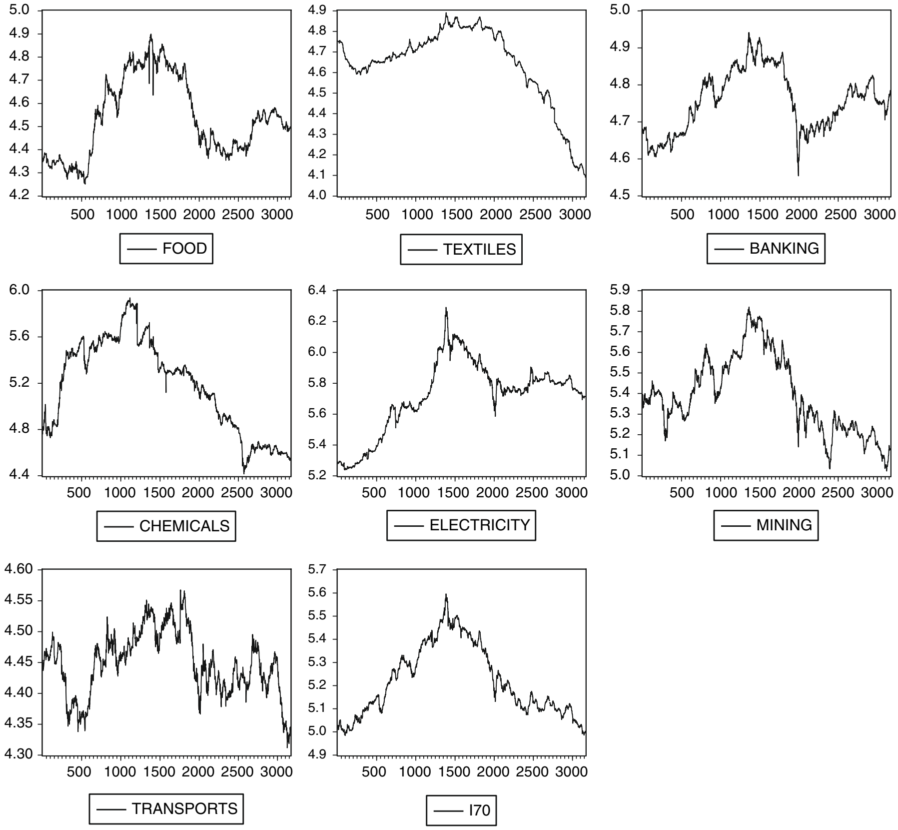

Fig. 1 Time series of seven sector indices and of the I70 index for the period January 2, 1901 to December, 29, 1911. Three thousand one hundred and sixty-four observations. Log-scale

sector of the last decade has been split in two series, the first being the Banking sector and the second being the simple average of the three most important financial sectors (Banking, insurance, financial holdings). The finance sector can indeed explain better the dynamics of the financial sector as a whole, even if it is less volatile than the banking sector itself.

Tables 3 and 4 provide summary statistics of sector and market indices. The characteristics of the returns vary consistently both across sectors and across time from 18.28% (Food) in the first decade and 34.26% (Chemical products) in the last one to −35.52% (Chemical products) in the first and −30.93% (Chemical products) in the last decade. Both indices, as expected, show lower returns (ranging from 6.25 and −7.77% to −6.72 and −8.11%, respectively). However, the volatility of the sectors—defined as the standard deviation of returns—of the first decade appears to be smaller than that of the last decade. Chemical Products sector is the most volatile among the first decade sectors while Cars, Media and Food are the most volatile sectors of the last decade. All series are not normally distributed and show evidence of skewness and leptokurtosis.

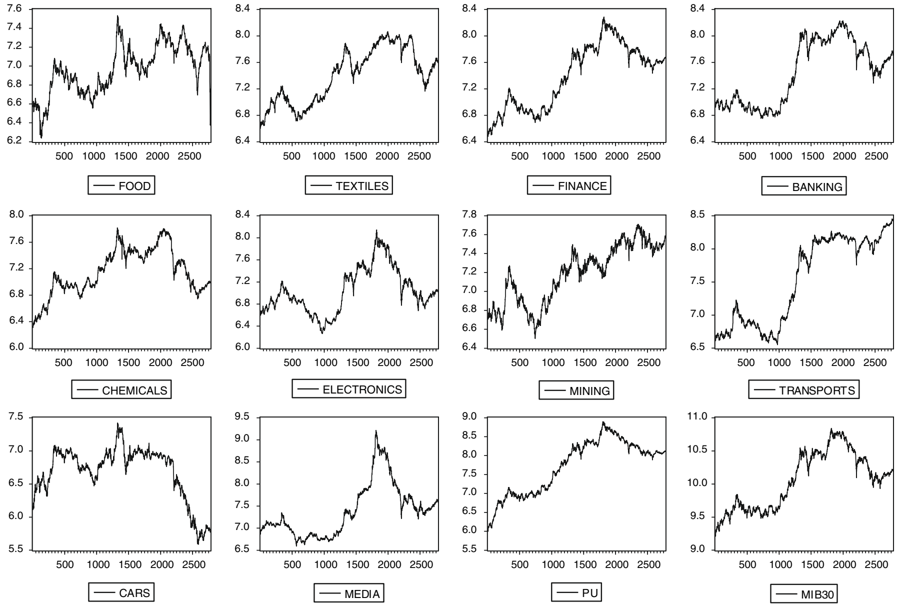

Fig. 2 Time series of ten sector indices and of Mib30 index for the period January 2, 1993 to February, 28, 2004. Three thousand and seventy-one observations. Log-scale

Table 3 Descriptive statistics for seven sectors and I70 returns (in logarithms) for the period January, 2, 1901 to December, 29, 1911 (Three thousand one hundred and sixty-four observations)

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Banking	0.003	2.825	−2.621	0.352	−0.751	14.134	16531.340	< 0.001
Chemicals	−0.005	16.215	−35.519	1.449	−6.020	157.307	3137184.000	< 0.001
Electricity	0.016	6.999	−4.925	0.634	0.513	19.720	36746.840	< 0.001
Food	0.009	18.281	−16.251	0.804	4.538	218.113	6070682.000	< 0.001
Mining	−0.009	6.808	−4.870	0.757	0.084	8.789	4392.803	< 0.001
Textiles	−0.020	2.116	−6.824	0.287	−5.564	117.219	1724687.000	< 0.001
Transports	−0.003	7.765	−2.769	0.425	1.611	42.280	203416.900	< 0.001
I70	0.002	6.248	−6.717	0.420	−0.257	46.090	243194.000	< 0.001

5 The results

Tables 5 and 6 show the results of a 2-states univariate Markov Switching Model on returns and volatility[7] for sector and global indices. The results show the existence of a regime 0 with low returns and high volatility and a regime 1 with high returns

[7] The parameters of the models are estimated by maximizing the conditional log-likelihood function evaluated using Hamilton's (1989) recursive procedure. All models are estimated using GAUSS codes and testing the robustness of the estimates by using different sets of initial values.

Table 4 Descriptive statistics for ten sectors and Mib30 returns (in logarithms) for the period January, 2, 1993- February, 28, 2004 (Three thousand and seventy-one observations)

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Banking	0.028	6.952	−9.317	1.420	−0.421	6.496	1495.241	< 0.001
Cars	−0.011	7.819	−9.615	1.767	−0.140	5.426	689.662	< 0.001
Chemicals	0.025	34.257	−30.933	1.646	0.537	116.478	1489062.000	< 0.001
Electronics	0.015	9.427	−8.426	1.671	−0.094	5.332	633.031	< 0.001
Finance	0.042	6.255	−8.519	1.371	−0.390	5.084	572.258	< 0.001
Food	−0.007	8.767	−27.142	1.728	−2.581	41.079	170742.000	< 0.001
Media	0.026	22.790	−11.067	1.778	0.716	16.507	21331.390	< 0.001
Mining	0.030	8.055	−10.454	1.546	−0.181	5.502	739.067	< 0.001
Public utilities	0.075	6.749	−13.527	1.630	−0.313	5.644	853.500	< 0.001
Textiles	0.036	5.439	−9.666	1.343	−0.468	6.477	1499.014	< 0.001
Transports	0.065	11.727	−14.263	1.348	−0.034	13.750	13362.050	< 0.001
MIB30	0.035	7.774	−8.107	1.527	−0.062	4.594	295.748	< 0.001

and low volatility.[8] This result is consistent with the evidence stressed by Brock et al. (1992) showing that buy signals are associated with returns which are higher and less volatile than sell signals.

On average, the last decade appears to be more volatile than the first one, confirming that the volatility has increased (Eichengreen and Bordo 2004); in particular, volatility of regime 1 increased almost by four times in a century. The chemicals in the first decade and the food sector in the last one appear to be under performing (lowest returns and highest volatility among the sectors considered).[9] Some sectors in the first decade of the twentieth century show a negative mean for the low volatility regime (Textiles and mining). In particular, mining results confirm historiography suggesting that it is one of the sectors driving the crash and one of the roots of the persisting crisis (Bonelli 1971; Baia Curioni 2000). The "New economy" sectors have a good performance: electric equipment in the first decade and media and Public Utilities[10] in the last one show means higher than the market index within each regime and almost the same volatility levels.

Tables 9 and 10 report the expected durations in both regimes. As expected, low volatility regimes are more persistent than high volatility regimes across time and sectors (Van Norden and Schaller 1997). In particular, the regimes are more persistent during the last decade. Note that, for example, the Mib30 expected duration of the high volatility regime during the last decade of the twentieth century is the same as

8 The evidence of the existence of regimes for the mean is quite weak for some sectors (for example, Food and Chemicals in the 1901–1911 decade and Finance, Mining and Transport in the 1993–2004 decade). Anyway, this is the specification that ensures the best results in the diagnostic tests so we preferred to keep it for all sectors.

9 The result of food is strongly influenced by the Parmalat crack: the food sector loses almost 70% from December, 11 to the end of 2003, until Parmalat is excluded by the Mib30.

10 Note that, in the last decade, Public Utilities sector includes the phone and mobile phone industry.

Table 5 Maximum likelihood estimates (standard error in parenthesis) based on data for daily Italian stock market (Sector and global indices) for the period January, 2, 1901 to December, 29, 1911

	μ_0	μ_1	σ_0	σ_1	P_{00}	P_{11}	Log L
Food	–0.002	0.064	5.286	0.161	0.60	0.95	−274.78
	(0.008)	(0.121)	(0.589)	(0.008)	(0.049)	(0.006)	
Textiles	–0.064	0.011	0.319	0.011	0.55	0.85	−3531.32
	(0.021)	(0.0006)	(0.021)	(0.0006)	(0.032)	(0.011)	
Banking	–0.050	0.017	0.45	0.036	0.85	0.96	−2490.21
	(0.026)	(0.004)	(0.032)	(0.001)	(0.020)	(0.005)	
Chemical products	–0.150	0.021	14.228	0.419	0.62	0.95	−1250.69
	(0.172)	(0.013)	(1.521)	(0.018)	(0.006)	(0.048)	
Electrical equipment	0.010	0.024	1.320	0.059	0.83	0.93	−1037.50
	(0.006)	(0.004)	(0.079)	(0.003)	(0.018)	(0.007)	
Mining	–0.015	–0.004	1.297	0.160	0.93	0.96	−196.84
	(0.039)	(0.011)	(0.073)	(0.009)	(0.011)	(0.006)	
Transport	–0.033	0.03	0.749	0.077	0.74	0.95	−1638.91
	(0.050)	(0.006)	(0.078)	(0.003)	(0.038)	(0.008)	
I70	–0.048	0.007	1.055	0.078	0.77	0.97	−1762.97
	(0.032)	(0.006)	(0.131)	(0.004)	(0.036)	(0.005)	

Table 6 Maximum likelihood estimates (standard error in parenthesis) based on data for daily Italian stock market (Sector and global indices) for the period January, 2, 1993 to February, 28, 2004

	μ_0	μ_1	σ_0	σ_1	P_{00}	P_{11}	Log L
Food	−0.520	0.035	18.347	1.701	0.85	0.99	−2526.99
	(0.428)	(0.030)	(3.924)	(0.077)	(0.061)	(0.003)	
Textiles	−0.186	0.099	4.376	1.046	0.95	0.98	−2000.23
	(0.094)	(0.024)	(0.409)	(0.044)	(0.020)	(0.004)	
Finance	−0.036	0.046	3.979	0.891	0.96	0.98	−2005.77
	(0.049)	(0.023)	(0.265)	(0.041)	(0.009)	(0.004)	
Banking	−0.015	0.046	4.634	0.967	0.96	0.98	−2080.53
	(0.068)	(0.026)	(0.469)	(0.086)	(0.011)	(0.006)	
Chemical products	−0.005	0.041	3.900	0.886	0.96	0.98	−2064.83
	(0.003)	(0.025)	(0.276)	(0.046)	(0.005)	(0.011)	
Electronic equipment	−0.038	0.044	5.610	1.232	0.97	0.99	−2529.72
	(0.005)	(0.003)	(0.424)	(0.081)	(0.008)	(0.004)	
Mining	−0.087	0.060	6.048	1.477	0.88	0.97	−2459.17
	(0.133)	(0.030)	(0.734)	(0.092)	(0.030)	(0.009)	
Transport/tourism	−0.039	0.024	5.397	1.240	0.98	0.98	−2748.77
	(0.030)	(0.026)	(0.277)	(0.065)	(0.005)	(0.006)	
Cars	−0.040	0.040	5.326	1.114	0.98	0.98	−1994.81
	(0.030)	(0.032)	(0.236)	(0.047)	(0.007)	(0.005)	
Media	0.018	0.048	5.785	1.104	0.97	0.99	−2496.18
	(0.002)	(0.010)	(0.051)	(0.501)	(0.008)	(0.003)	
Public utilities	0.020	0.146	4.256	1.225	0.98	0.98	−2599.98
	(0.012)	(0.056)	(0.221)	(0.068)	(0.006)	(0.005)	
Mib30	0.012	0.048	4.289	1.213	0.97	0.99	−2384.97
	(0.006)	(0.030)	(0.251)	(0.056)	(0.007)	(0.004)	

Table 7 Specification tests based on data for daily Italian stock market (Sector and global indices) for the period January, 2, 1901 to December, 29, 1911

	Food	Textiles	Banking	Chemicals	Electric Eq.	Mining	Transport	I70
Serial correlation: regime 0	5.596	10.897	24.871	5.598	5.207	19.490	4.747	46.395
	(0.935)	(0.538)	(0.015)	(0.935)	(0.951)	(0.077)	(0.966)	(0.000)
Serial correlation: regime 1	27.301	3.349	2.953	0.457	29.800	0.291	6.223	4.325
	(0.007)	(0.993)	(0.996)	(0.997)	(0.003)	(0.997)	(0.904)	(0.977)
ARCH effects: regime 0	10.637	4.903	0.070	1.502	17.723	1.446	10.596	6.535
	(0.031)	(0.297)	(0.999)	(0.826)	(0.001)	(0.836)	(0.031)	(0.163)
ARCH effects: regime 1	7.258	4.924	3.601	1.287	17.652	1.241	13.931	23.303
	(0.123)	(0.295)	(0.463)	(0.864)	(0.001)	(0.871)	(0.008)	(0.000)
LM test for ac across regimes	3.187	1.640	2.776	0.418	2.014	4.010	2.282	1.694
	(0.074)	(0.200)	(0.096)	(0.518)	(0.156)	(0.045)	(0.131)	(0.193)
LM test for ARCH	0.384	3.924	3.101	1.287	1.652	1.241	0.839	0.626
	(0.535)	(0.048)	(0.078)	(0.257)	(0.199)	(0.265)	(0.360)	(0.429)

LM ARCH test statistic with 4 lags and Ljung–Box 12-lag autocorrelation test statistic. *P* values in parenthesis

the I70 expected duration of the low volatility regime of the first decade (33 days). Banking shows the highest expected duration among the sectors of the first decade of the twentieth century (25 days duration of the low volatility regime), which is still very low compared to that of the last decade, since no sector shows a duration lower than 33 days between 1993 and 2004. This implies that between 1901 and 1911 the transition from a state to the other occurred for a short period of time, confirming Bonelli (1971) about the uncertain situation in the Italian stock market during the 1907 crisis: it is the starting point of a depression that lasted until 1914.

For a good specification of the model, Tables 7 and 8 show the diagnostic proposed by Hamilton (1996), testing for serial autocorrelation and ARCH effects within and between the regimes.

As an illustration of switching behavior, a plot of the smoothed probability to be in a high volatility regime (give that at time $t-1$ the sector was in the high volatility regime) is displayed for each sector and global index. When the graph displays sharp spikes at irregular intervals, suggesting that the transition from the low to the high volatility regime occurs for a very short period of time, that sector is categorized as a sector showing *weak regimes*. The graphs show the existence of weak regimes especially for food (1901–1911), chemicals (1901–1911) and food (1993–2004). The smoothed probabilities representation is coherent with the timing of crashes in both periods, showing the highest transition probability from low to high volatility regime immediately before 1901, 1905, 1907 and before 1994, 1997 and 2001.[11]

[11] The food sector is strongly influenced by the Parmalat crack. In particular, if the last two months are excluded from the sample, the volatility is reduced by 50%, the mean of the high volatility regime becomes positive (from −0.52 to 0.13) while the expected duration of the high volatility regime increases from 6.7 to 10 days. Results are available upon request.

Table 8 Specification tests based on data for daily Italian stock market (Sector and global indices) for the period January, 2, 1993 to February, 28, 2004

	Chemicals	Mining	Banking	Electronic Eq.	Transport	Food	Textiles	Cars	Media	P. U.	Finance	Mib30
Serial correlation: regime 0	7.800	7.275	2.903	6.977	6.684	89.020	13.531	5.052	8.688	7.777	8.184	14.507
	(0.801)	(0.839)	(0.996)	(0.000)	(0.878)	(0.000)	(0.332)	(0.956)	(0.729)	(0.802)	(0.771)	(0.270)
Serial correlation: regime 1	0.395	10.966	1.668	30.353	2.263	8.674	12.185	4.065	7.505	4.992	8.906	0.315
	(1.000)	(0.532)	(1.000)	(0.002)	(0.999)	(0.731)	(0.431)	(0.982)	(0.823)	(0.958)	(0.711)	(1.000)
ARCH effects: regime 0	3.851	1.789	9.305	1.651	2.612	1.442	6.335	8.954	4.193	1.513	0.564	8.603
	(0.427)	(0.775)	(0.054)	(0.800)	(0.625)	(0.837)	(0.176)	(0.062)	(0.381)	(0.824)	(0.967)	(0.072)
ARCH effects: regime 1	3.877	3.896	5.314	4.071	2.469	5.488	6.174	15.354	3.833	1.539	7.812	6.468
	(0.423)	(0.420)	(0.257)	(0.397)	(0.650)	(0.241)	(0.187)	(0.004)	(0.429)	(0.820)	(0.099)	(0.167)
Autocorrelation across regimes	1.620	0.946	0.023	1.620	0.093	1.913	1.189	2.103	3.736	2.504	3.815	1.678
	(0.203)	(0.331)	(0.879)	(0.203)	(0.761)	(0.167)	(0.275)	(0.147)	(0.053)	(0.114)	(0.051)	(0.195)
LM test for ARCH	3.399	3.896	2.314	3.399	2.469	3.488	2.221	1.354	3.832	1.539	2.812	1.288
	(0.065)	(0.048)	(0.128)	(0.065)	(0.116)	(0.062)	(0.136)	(0.245)	(0.050)	(0.215)	(0.094)	(0.256)

LM ARCH test statistic with 4 lags and Ljung–Box 12-lag autocorrelation test statistic. P values in parenthesis

Table 9 Durations in days for the period January, 2, 1901 to December, 29, 1911

	d_0	d_1
Food	2.6	20
Textiles	2.3	7.1
Banking	6.7	25
Chemical products	2.6	20
Electric equipments	1.2	16.7
Mining	2.5	14.3
Transport	3.8	20
I70	4.3	33.3

Table 10 Durations in days for the period January, 2, 1993 to February, 28, 2004

	d_0	d_1
Food	10	33.3
Textiles	20	100
Finance	25	100
Banking	25	50
Chemical products	25	50
Electronic equipments	33.3	100
Mining	7.7	33.3
Transport	50	50
Cars	50	50
Media	33.3	100
Public utilities	50	50
Mib30	33.3	100

Table 11 Multivariate transition probability matrix (1901–1911)

States	0	1
0	0.55	0.45
	(0.050)	(0.065)
1	0.14	0.86
	(0.081)	(0.003)

Table 12 Multivariate transition probability matrix (1993–2003)

States	0	1
0	0.71	0.29
	(0.034)	(0.073)
1	0.09	0.91
	(0.040)	(0.002)

Let us now introduce the results of the multivariate 2-state Markov Switching model. Tables 11 and 12 show the transition probability matrices for the first and the last decade of the twentieth century. The multivariate analysis confirms that the low volatility regime is more persistent than the higher volatility regime independently of

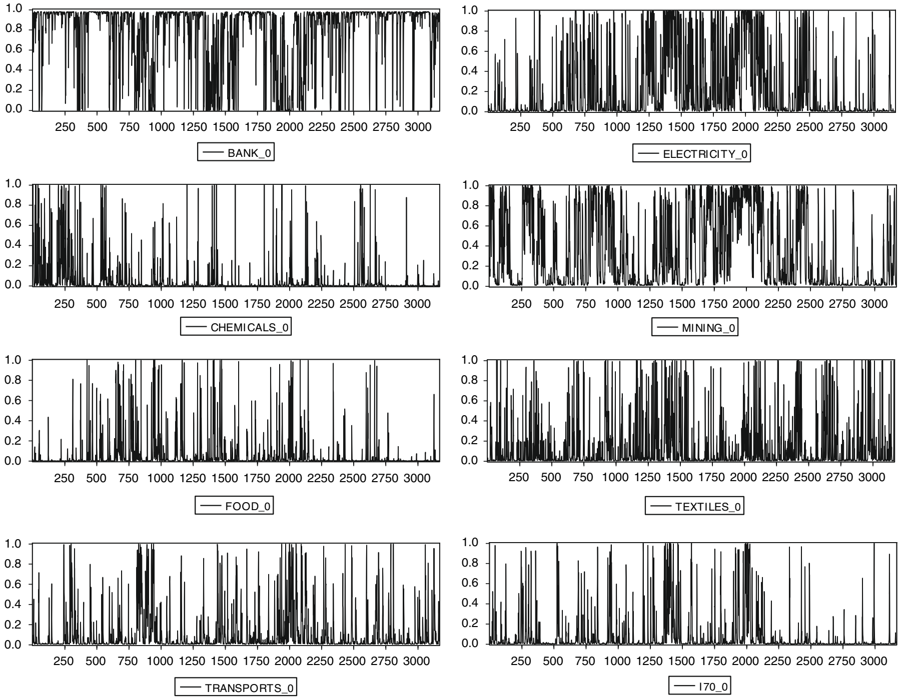

Fig. 3 Smoothed probability (Regime 0): 1901–1911

the decade ($P_{00} = 55\%$, $P_{11} = 86\%$ and $P_{00} = 71\%$, $P_{11} = 91\%$, respectively), showing also the higher stability of the regimes in the last decade. From the multivariate analysis, linear relationships between sectors across the regimes over a century can be detected (Tables 13, 14). The correlations between sectors of the first decade are lower than those of the last decade, independently of the regimes. As expected, the correlation increases as the volatility increases, in both the first and the last decade of the century. Banking shows the highest correlations with the remaining sectors over the century, confirming its central role in the Italian economy.

From Table 13, some relationships can be stressed. Chemicals and food and chemicals and transports (from 0.20 to 0.25, from 0.16 to 0.26 and from 0.15 to 0.24, respectively) relationships show the impact of chemical innovations on food industry and transports, while the link between food and textiles confirm the relationship between two of the most relevant traditional sectors. Electrical equipment sector shows an increasing correlation with food (from 0.10 to 0.24), with banking (from 0.07 to 0.14) and with transports (from 0.15 to 0.24), suggesting a central role of electricity during the "Second industrial revolution". Finally, the mining, the food and the textile sectors show quite strong relationships with the banking sector, increasing from the low to the high volatility regime. This conclusion is consistent with the results of the factor analysis in Baia Curioni (2000) that identifies banking, mining, textiles and food as the most risky sectors during this period.

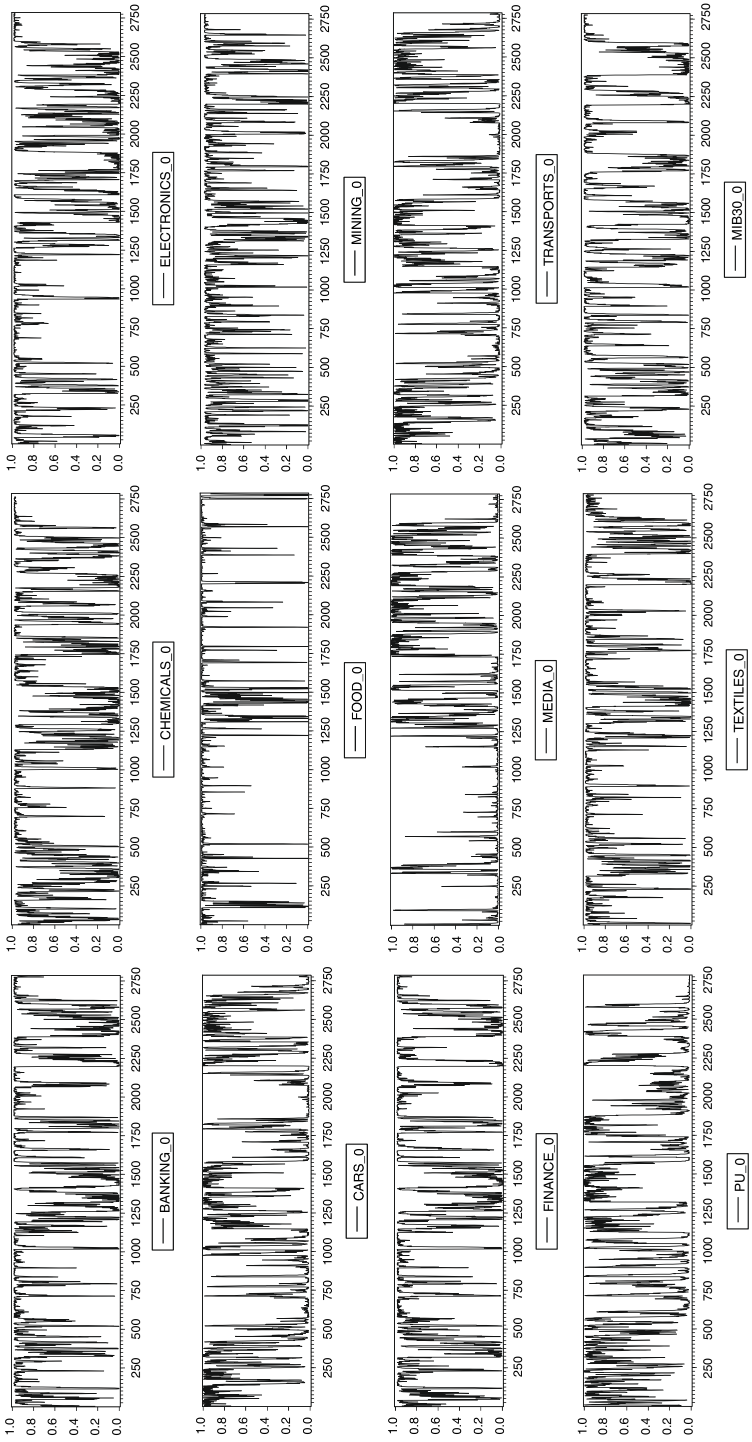

Fig. 4 Smoothed probability (Regime 0): 1993–2004

Table 13 Correlation matrix (1901–1911)

Regime 0	Textiles	Food	Transport	Electricity	Banking	Mining	Chemicals
Textiles	1	0.25	0.20	0.08	0.17	0.07	0.10
Food		1	0.22	0.24	0.31	0.03	0.26
Transport			1	0.20	0.03	0.09	0.24
Electricity				1	0.14	0.07	0.15
Banking					1	0.22	0.07
Mining						1	0.03
Chemicals							1
Regime 1	Textiles	Food	Transport	Electricity	Banking	Mining	Chemicals
Textiles	1	0.20	0.19	0.12	0.01	0.02	0.09
Food		1	0.43	0.10	0.03	0.12	0.16
Transport			1	0.15	0.007	0.06	0.15
Electricity				1	0.07	0.07	0.08
Banking					1	0.20	0.21
Mining						1	0.08
Chemicals							1

Table 14 shows that the correlations between sectors during the century increase, as expected (Eichengreen and Bordo 2004). Focusing on the last decade, the correlations from the low to the high volatility regime increase. For example public utilities and banking correlation shifts from 0.37 to 0.70 and media and electronic equipment increases from 0.55 to 0.62. Banking is still strongly linked with all other sectors. Concerning the "New economy" sectors, we might stress that public utilities shows a high correlation with media and electronic equipment in both regimes (from 0.53 to 0.55 and from 0.70 to 0.68, respectively).

From the results, a comparison between 1901–1911 and 1993–2004 periods can be established. The central role of the Banking system in the Italian economy persists over the century, financing the the most innovative sectors ("New economy" sectors) in both periods, even if with alternate results as shown by the Mining case between 1901 and 1911, culminated with the nationalization of the sector in 1905. The "New economy" sectors in both periods have a good performance in the Italian financial market: electric equipment in the first decade and public utilities, media and electronic equipment in the last decade of the century perform better than the traditional sectors (textiles and food in both periods).

6 Conclusive remarks

Looking for the roots of the increased volatility in the Italian stock market over the long run, we compare two high volatility periods representing the "Second" and the "Third industrial revolution" (1901–1911 and 1993–2004), both characterized by the introduction of strong technological innovations and by high volatility in the financial

Table 14 Correlation matrix (1993–2004)

Regime 0	Food	Cars	Chemicals	Electronic Eq.	Mining	Textiles	P.U.	Media	Transport	Finance	Bank
Food	1	0.46	0.35	0.37	0.34	0.46	0.40	0.28	0.42	0.46	0.58
Cars		1	0.48	0.50	0.43	0.61	0.54	0.38	0.49	0.60	0.65
Chemicals			1	0.47	0.33	0.48	0.45	0.32	0.38	0.51	0.99
Electronic Eq.				1	0.25	0.58	0.68	0.62	0.51	0.82	0.63
Mining					1	0.42	0.35	0.22	0.40	0.56	0.49
Textiles						1	0.61	0.48	0.55	0.66	0.62
P.U.							1	0.55	0.43	0.92	0.70
Media								1	0.41	0.61	0.49
Transport									1	0.57	0.54
Finance										1	
Bank											1

Regime 1	Food	Cars	Chemicals	Electronic Eq.	Mining	Textiles	P.U.	Media	Transport	Finance	Bank
Food	1	0.52	0.60	0.48	0.47	0.49	0.61	0.31	0.47	0.62	0.26
Cars		1	0.67	0.59	0.49	0.56	0.65	0.45	0.46	0.68	0.41
Chemicals			1	0.66	0.55	0.61	0.75	0.50	0.51	0.77	0.99
Electrical Eq.				1	0.46	0.57	0.70	0.55	0.47	0.80	0.41
Mining					1	0.46	0.60	0.40	0.45	0.79	0.31
Textiles						1	0.63	0.47	0.43	0.65	0.40
P.U.							1	0.53	0.37	0.94	0.37
Media								1	0.33	0.58	0.24
Transport									1	0.58	0.28
Finance										1	
Bank											1

markets. We use Markov Switching Models—models where the conditional variance/mean switches across a number of states and the dynamics of the switches is driven by a latent Markov Chain. We test the existence of regimes on the mean and volatility (high and low) and we describe the effects of regime switches in the Italian stock market over the century for sector and global indices.

The last decade appears to be more volatile than the first one (Eichengreen and Bordo 2004): the volatility of the high volatility regime increased almost by four times in a century. As expected, low volatility regimes are more persistent than high volatility regimes both across time and sectors (Van Norden and Schaller 1997). In particular, the regimes have become more persistent during the last decade.

The results show that the "New economy" sectors—electricity in the 1901–1911 decade and electronic equipment, media and public Utilities for the 1993–2004 decade—perform well in both periods with stable regimes. On the contrary, traditional sectors, like Textiles and Food, strongly under perform, showing also weak regimes. The Banking sector maintains a crucial role over the century with high volatility and strongly persistent regimes in both periods.

Finally, the multivariate approach shows the correlation dynamics between the sectors, across the regimes. The correlations between sectors increase over time. As expected, the Banking sector has a central role in both periods, showing high correlations with all sectors independently of the regimes. Indeed, Banking is very important for the Italian economy (a *bank-oriented* economy), financing the "New economy" sectors in both periods (Media, public utilities and electronic equipment, and electrical equipment and chemicals, respectively).

A final observation may be advanced on the basis of this long run analysis on Italian financial market. The extraordinary evolution in financial markets improved very poorly the reactions after the shocks which, in turn, increased dramatically over a century. The Italian financial market is not less risky than a century ago; it is more reactive and sensitive to international shocks but it is still fragile and banking oriented.

References

Baia Curioni S (1995) Regolazione e competizione. Storia del Mercato Azionario in Italia (1908–1938). Bologna, Il Mulino

Baia Curioni S (2000) Modernizzazione e Mercato: la Borsa di Milano nella "nuova economia" dell'età giolittiana (1888–1914). Milano, E.G.E.A

Baillie RT, Bollerslev T, Mikkelsen HOA (1996) Fractionally integrated generalized autoregressive conditional heteroskedasticity. J Econometr 74/1:3–30

Billio M, Pelizzon L (1997) Pricing option with switching regime volatility, Nota di Lavoro 97.07. Dipartimento di Scienze Economiche, University of Venice

Billio M, Pelizzon L (2000) Value-at-Risk: a multivariate switching regime approach. J Empir Fin 7:531–554

Bollerlsev T (1986) Generalized autoregressive conditional heteroskedasticity. J Econometr 31:307–327

Bonelli F (1971) La crisi del 1907, una tappa dello sviluppo industriale italiano. Fondazione Einaudi, Torino

Bordo M (1986) Financial crises, banking crises, stock market crashes and the money supply: some international evidence, 1870–1933. In: Capie F, Wood GE (eds) Financial crises and the world banking system. St. Martin's Press, New York pp 190–248

Bordo M, Eichengreen B, Klingebiel K, Martinez Peria S (2001) Is the crisis problem growing more severe? Econ Policy 24:51–82

Bordo M, Murshid A (2001) Are financial crises becoming more contagious: What is the historical evidence on contagion? In: Claessens S, Forbes KJ (eds) International financial contagion. Kluwer, Boston pp 367–428

Brock WA, Lakonishok J, Le Baron B (1992) Simple technical trading rules and the stochastic properties of stock returns. J Fin 47:1731–1764

Castronovo V (1995) Storia economica d'Italia. Einaudi, Torino

Confalonieri A (1982) Banca e Industria in Italia dalla crisi del 1907 all'Agosto 1914. Banca Commerciale Italiana, Milano

Cotula F, Garofalo P (1996) Le Aziende di Credito nel Sistema Finanziario Italiano. Aggregati Monetari e Creditizi. Concentrazione e Conti Economici delle Banche. I Bilanci delle Aziende di Credito 1890–1936, a cura di Cotula, F., Roma-Bari, Laterza

Delargy PJR, Goodhart C (1999) Financial Crises: Plus ça change, plus c'est la même chose. Special Paper no. 108, LSE Financial Group

De Long B (2001) Financial crises in the 1890s and 1990s. We remember history: Why are we still condemned to repeat it? University of Berkeley, Mimeo

De Luca G (2002) Dall'economia industriale all' "industria" della finanza: le società quotate al listino azionario della Borsa di Milano dal 1861 al 2000. In: De Luca G (ed) Le Società Quotate alla Borsa Valori di Milano dal 1861 al 2000. Milano, Centro per la cultura d'impresa, Libri Scheiwiller

Eichengreen B, Bordo M (2004) Crises now and then: What lessons from the last era of financial globalization? In: Mizen P (ed) Monetary history, exchange rates and financial markets. Edward, Edgar

Engle RF (1982) Autoregressive conditional heteroskhedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50(4):987–1007

Engle RF, Kroner K (1995) Multivariate simultaneous GARCH. Econometr Theory 11:251–276

Gallo GM, Otranto E (2007) Volatility transmission across markets: a multi-chain Markov Switching Model. Appl Fin Econ 17:659–670

Glosten LR, Jagannathan R, Runkle DE (1993) On the relation between expected value and the nominal excess return on stocks. J Fin 48:1779–1801

Hamilton JD (1989) A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57:357–384

Hamilton JD (1994) Time series analysis. Princeton University Press, New Jersey

Hamilton JD, Susmel R (1994) Autoregressive conditional heteroskedasticity and changes in regime. J Econometr 64:307–333

Hamilton JD (1996) Specification tests in Markov switching time series models. J Econometr 70:127–57

Jeanne O, Masson P (2000) Currency crises, sunspots and Markov switching regimes. J Int Econ 50(2):327–350

Khabie-Zeitoun D, Salkin G, Cristofides N (1999) Factor GARCH, regime switching and term structure models. In: Proceedings FFM99, London

Kim C-J (1993) Dynamic linear models with Markov switching. J Econometr 60:1–22

Kuo C-J, Lu S-L (2005) Taiwan's financial holding companies: an empirical investigation based on Markov regime-switching model. Appl Econ 37:593–605

La Francesca S (2004) Storia del Sistema Bancario Italiano. Bologna, Il Mulino

Mills TC, Wang P (2003) Multivariate Markov switching common factor models for the UK. Bull Econ Res 55(2):177–193

Nelson DB (1991) Conditional heteroskedasticity in asset returns: a new approach. Econometrica 59:347–370

Rabemanajara R, Zakoïan JM (1993) Threshold ARCH models and asymmetries in volatility. J Appl Econometr 1:31–49

Rockinger M (1994) Switching regressions of unexpected macroeconomic events explaining the French stock index. HEC

Siciliano G (2001) Cento Anni di Borsa in Italia. Bologna, Il Mulino

Van Norden S, Schaller H (1997) Regime switching in stock market returns. Appl Fin Econ 7:177–191

Wilson J, Sylla R, Jones C (1990) Financial market panics and volatility in the long run, 1830–1988. In: White E (ed) Crashes and panics. Dow-Jones Irwin, Illinois pp 85–125

Zakoïan JM (1994) Threshold heteroskedastic models. J Econ Dyn Control 18:931–955