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On Chinese stock markets: How have they evolved along time?

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Abstract

China is the largest emerging capital market with a unique setup: it issues simultaneously both (i) Class A shares addressed to Chinese domestic investors, and (ii) Class B Shares addressed to foreign investors. After Chinese stock resumed the operation, they feature dramatic fluctuations due to policy changes and over-speculative activity of individual investors. This paper aims to analyse the evolution of both the Shanghai A and B Markets through a Markov-Switching asymmetric GARCH in four different time frames.

Keywords: China stock market; Markov-Switching asymmetric GARCH; volatility

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1. Introduction

China, 1949. A successful Mao Zedong seized power and, for the sake of transforming the country into a Communist Economy, decided to close the national Financial Markets.

In 1978, Deng Xiaoping, the Mao's successor, initiated an Economic Reformation to modernise and open the nation gradually. Doing so, Chinese stock markets were resuming, growing rapidly and becoming the largest emerging capital market in the world.

Chinese stock markets have a unique setup never featured before. It issues two class of shares, sometimes called "twin" shares since they have the same rights: (i) Class A shares addressed to Chinese domestic investors and traded in national currency, and (ii) Class B Shares addressed to foreign investors, traded in USD (Shanghai) and HKD (Shenzhen). Beside nationality of investors, the main difference is the size of each market: Market A is much larger than market B (integrated by less than a hundred firms). The aim of this unique design is to reduce the potential uncertainty due to exposure to overseas capital markets after having closed frontiers for several decades. Hence, creating segmented markets gives to foreigners the opportunity to invest in China and, at the same time, it would prevent foreign investors from controlling the Chinese national market. On the other hand, Market A would benefit as well from this configuration, since the impact of international shocks are expected to be absorbed in Market B, minimising their impact on Market A. This design allowed Chinese stock markets a lighter development, reducing possible risk spillovers and financial contagion from international markets.

Beside the configuration of Chinese stock markets, one of the most attractive fields of study is the behaviour of local investors. According to Kang et al. (2002), national investors take decisions mainly driven by market rumours and individuals' sentiment, which induces a greater quantity of return reversals than when the market is driven by information, mainly (as it occurs in developed stock markets). A fact that, together with non-reliable information of listed firms (Hu, 1999), affects the market performance, inducing investors' losses due their lack of real data. Hence, with the aim of avoiding these not desirable behaviour, the Chinese government becomes an active part of the market impulsing legal reforms to control and stabilise the market.

Note that the aforementioned characteristics of Chinese stocks markets may lead a really unstable market, showing dramatic fluctuations every now and then. This performance is reflected via the volatility of the market, which is usually estimated through the standard GARCH framework. However, since we may find abrupt returns reversals, vaguely informed investors and several legal reforms to control the market, the standard GARCH framework is not powerful enough. Therefore, it lead us to a deeper volatility analysis through a Asymmetric Markov-Switching GARCH, which enables us to a better insight of the volatility structure. Firstly, each studied period has two regimes (high and low volatility), including different news impact coefficients which capture the influence of bad and good news. Secondly, the estimation of the model also includes the transition matrix between states, element that informs on how the system can move from one state to another in terms of probability. Finally, considering that Chinese stock markets are heavily tailed, estimations utilise the Student t distribution as conditional distribution.

By using this approach, the current paper answers the following questions: How have the Chinese stock markets evolved? Are the legal reforms effective? Is the behaviour of Market B different from Market A? Are the markets becoming more mature as time goes by? Are they really driven by sentiments? If so, is this behaviour fading away as time evolves?

The structure of the paper is as follows: Section 2 reviews literature and some historical facts regarding Chinese stock markets. Section 3 presents the econometric framework. Section 4 provides the Data and main results. Finally, Section 5 concludes.

2. Literature review and some historical notes

Reopening Chinese stock markets stimulates investors' attention, as there is a new location to (apparently) make profits just by buying and selling. New investors were optimistic and began to operate in such attractive markets. Nonetheless, things did not happen as expected, and the markets suffers abrupt peaks an lows. Thenceforth, China impulsed some legal reformations on the stock markets with the purpose of controlling the market performance.

Specifically, during the first years, Chinese authorities tested the behavior of the market when changing price limitations, defining a final price limit of +/- 10%. Between 1997 and 2007, several modifications on transaction costs were undertaken. On May 10, 1997, the tax rate was raised to 0.5%, then, lowered to 0.4% percent in June, 1998, then, adjusted to 0.3% after a year, and, fixed to 0.2% in 2001. In this regard, Baltagi et al. (2006) analysed the effect of these policy changes and concluded that they increased volatility. Later, in 2005 the government further lowered again the stamp tax to 0.1%, and raised it to 0.3% in 2007 to cool down an overheated market. Finally, in April 2008 transaction costs reached 0.1% for the second time, and 5 months later the Ministry of Finance and the State Administration of Taxation decided to cancel the share trading stamp tax on stock purchase while the stamp tax on share selling remained unchanged at 0.1% percent.

Additionally, in early 2000s, the local government made two major policy changes in both A and B markets. In 2001 the government tried to boost Market B by giving access to national citizens holding foreign currency, and in 2003 China opened Market A to foreigners under the *QFII* program, which allows foreign **qualified** institutional investors to hold A shares after the national authority approval.

Chinese legal reformations are interesting to analyze as the government is gradually moving further from the initial segmentation. Actually, both policy changes were really well designed: (i) introducing foreign qualified institutional investors to Market A could improve the performance of the market, always under the hypothesis that institutional investors manage better the available information and trade more rationally (taking into the account that the China government controls the access of the foreign institutional investors); (ii) allowing domestic investors holding foreign currency to join Market B achieves inflows of USD and HKD into Chinese financial system.

As a consequence of the aforementioned policy changes, the huge amount of speculative capital and the over-speculative activity of individual investors, A and B stock markets have been featured dramatic market fluctuations. For instance the following facts, among others, influenced the performance of the market: (i) during the first four years after resuming the stock markets, four important volatility spikes can be identified in A and B markets due to policy changes related to daily price change limit; (ii) in 1996, press reports suggested that Chinese national investors began investing illegally in Market B, forcing Chinese government to impose several new restrictions to control excessive speculation, and reintroduce price variation limits by the end of the year; (iii) after changing the legislation on B market in 2001 there was a massive withdrawal of overseas investors, fact that cause a sharp drop on B market.

Therefore, volatility of A and B markets is an attractive and actual field to study, as the recently raising literature regarding Chinese markets reflects. After reviewing this literature we can find out some conclusions.

Mean returns on Chinese markets have found mainly positive in the literature (Lee et al., 2001, Chiang et al., 2009, among others) but basically not statistically significant as stated by Hou (2010). According to Wang and Jiang (2004) Chinese markets display the highest standard deviation in Asian and Pacific Markets, specially B markets, although volatility decreases as we move further form 1997 (Panetta et al., 2006).

Regarding asymmetry, Mookerjee and Yu (1999), Wang and Jiang (2004), Chiang et al. (2009) find positive skewness of the empirical distribution of returns. Only Hou (2010) finds the opposite fact, showing that Composite Chinese indices display negative skewness during 1997-2007.

Concerning kurtosis, literature agrees that China exhibits high level of kurtosis and heavy tails (Mookerjee and Yu, 1999).

Finally, Koutmos (1999), Chiang and Doong (2001), Friedmann and Sanddorf-Köhle (2002), Huang and Zhu (2004), Hou (2010) find evidence on asymmetric behavior of the volatility, and concludes that negative innovations have a greater impact on volatility. Results on risk-return premium vary among the chosen period and stock market: De Santis and Imrohoroglu (1997) find no relationship between returns and volatility, while Lee et al. (2001) concludes a negative risk-return relationship in Shanghai A, and Fabozzi et al. (2004) and Loudon (2006) find positive risk-return relationship in both, Shanghai and Shenzhen, stock markets.

3. Econometric Review

Volatility estimation has played a central role in uncertainty and risk management, as miscalculating the potential losses of financial assets leads investor to wrong decisions. Indeed, as Mandelbrot and Hudson (2014) points out, after one investment is made, the profit ratio is lower than initially calculated, benefits are below expectations and risk turns are much higher, and that happens several time for a huge number of individuals, in different financial markets worldwide.

In this context, Engle (1982) provides an answer to changing volatility in financial time series with the ARCH model, where the present variance it is a function of past innovations (ε). Since then, ARCH models grew rapidly into a rich family of empirical models for volatility forecasting during the last two decades. Bollerslev (1986) generalized the ARCH model of Engle, the well known GARCH model, which extends the specification of the conditional variance of Engle (1982), allowing the conditional variance to depend on its past values, which renders the model more parsimonious than the ARCH model. Hence, the general equation of a GARCH(p,q) is given by:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \cdot h_{t-j}$$

where p is the number of lags of the past variance and q is the number of lags of past innovations. Note that in case we choose a GARCH(1,1) the conditional variance equation is specified as follows,[1]

$$h_t = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot h_{t-1}$$

where α measures the *news* impact in the variance, and β is the *decay* parameter of the variance. The GARCH model mimics better the behaviour

[1] Indeed, in most empirical applications, the GARCH(1,1) is enough to reproduce the volatility dynamics of financial data, fact that led the GARCH(1,1) to become the "workhorse" model by both academics and practitioners.

of financial volatility; and becomes more powerful thanks to the qualitative side of estimated magnitudes. According to Alexander (2009) the GARCH coefficients have a natural interpretation in terms of the reaction to market shocks and the mean reversion of volatility following a shock:

- The *news impact* α measures the reaction of conditional volatility to market shocks. When α is relatively large (e.g. above 0.1) then volatility is very sensitive to market events.
- The *decay parameter* β measures the persistence in conditional volatility irrespective of anything happening in the market. When β is relatively large (e.g. above 0.9) then volatility takes a long time to die out following a crisis in the market.
- The sum $\alpha + \beta$ is called persistence, and determines the rate of convergence of the conditional volatility to the long term average level. When the persistence is relatively large (e.g. above 0.99) then the terms structure of volatility forecasts from the GARCH model is relatively flat.
- The GARCH constant parameter ω, together with the persistence, determines the level of the long term average volatility, i.e. the unconditional variance in the GARCH model, h_y. When $\frac{\omega}{1-\alpha-\beta}$ is relatively large, then the long term volatility, σ_y, in the market is relatively high.

Numerous refinements and extensions have been made to the GARCH model to capture better financial stylized facts. For instance, the EGARCH (Nelson, 1991), the TGARCH (Zakoian, 1994), and the QGARCH (Sentana, 1995) models. Among them, we highlight the GJR GARCH (Glosten et al., 1993), which features and asymmetric coefficient to take into account the impact of negative innovations. Therefore the original GARCH(1,1) is as follows:

$$h_t = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot h_{t-1} + \underbrace{\tau \cdot I(\cdot)\varepsilon_{t-1}^2}_{\text{asymmetric term}}$$

where: $\omega > 0$, $\alpha \geqslant 0$, $\beta \geqslant 0$, y $\tau \in [-1, 1]$; $I(\cdot)$ is a dicotomic function depending on the sign of ε_{t-1},

$$I = \begin{cases} 1 & \text{if} \quad \varepsilon_{t-1} < 0 \\ 0 & \text{if} \quad \varepsilon_{t-1} \geqslant 0 \end{cases}$$

The asymmetric behavior of h_t determines the News Impact Curve (NIC) proposed by Engle and Ng (1993),

$$NIC = \begin{cases} \omega + \beta \cdot h_y + (\alpha + \tau) \cdot \varepsilon_{t-1}^2 & \text{if} \quad \varepsilon_{t-1} < 0 \\ \omega + \beta \cdot h_y + \alpha \cdot \varepsilon_{t-1}^2 & \text{if} \quad \varepsilon_{t-1} \geqslant 0 \end{cases}$$

Unfortunately, even the application of the GJR-GARCH cannot guarantee a full explanation of the volatility process of stock returns. Actually, the application of GARCH to long time series of stock-return data will yield a high measure of persistence because of the presence of structural changes in the parameters. To overcome this drawback, in recent years the Markov-switching GARCH models have been developed, as they provide an explanation of the high persistence in volatility (i.e., nearly unit root process for the conditional variance) observed with single-regime GARCH models (Ardia, 2008). In these models a hidden Markov sequence {st} with state space {1,...,K} allows discrete changes in the model parameters (allowing for a quick change in the volatility level which leads to significant improvements in volatility forecasts). Another strength of splitting the conditional variance in different regimes is that one can see significant differences in the GARCH parameters. This is illustrated by Haas et al. (2004) who states that: "a relatively large value of α_1^k and relatively low values of β^k in high-volatility regimes may indicate a tendency to over-react to news, compared to regular periods, while there is less memory in these sub-processes."

Ardia (2008) defines a Markov-switching GARCH with two different regimes: regime 1 for low volatility and regime 2 for high volatility. His model also includes asymmetric behavior of the conditional variance: it contains two news impact parameters, $\boldsymbol{\alpha}^+$ for positive returns and $\boldsymbol{\alpha}^-$ for negative returns; so, when $\boldsymbol{\alpha}^- > \boldsymbol{\alpha}^+$ there exists the *leverage effect*. Furthermore, the conditional distribution of innovations is the Student-t with ψ degrees of freedom. The whole specification of this model is as follows:

$$\begin{aligned} y_t &= \varepsilon_t \cdot (\varphi h_t)^{1/2} \\ \varepsilon_t &\sim \mathcal{S}(0,1,\psi) \\ \varphi &= \frac{\psi - 2}{\psi} \\ h_{t,i} &= \begin{cases} \omega_1 + (\alpha_1^+ 1_{\{\varepsilon_{t-1} \geqslant 0\}} + \alpha_1^- 1_{\{\varepsilon_{t-1} < 0\}}) \cdot \varepsilon_{t-1}^2 + \beta_1 \cdot h_{1,t-1} & \text{when} \quad s_t = 1 \\ \omega_2 + (\alpha_2^+ 1_{\{\varepsilon_{t-1} \geqslant 0\}} + \alpha_2^- 1_{\{\varepsilon_{t-1} < 0\}}) \cdot \varepsilon_{t-1}^2 + \beta_2 \cdot h_{2,t-1} & \text{when} \quad s_t = 2 \end{cases} \end{aligned}$$

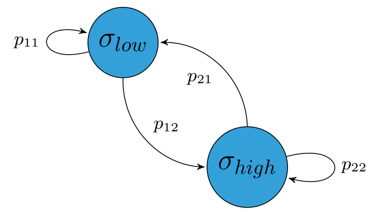

Figure 1: **Markov-Switching with two regimes: low $\sigma_{\mathbf{low}}$ and high volatility $\sigma_{\mathbf{high}}$.** p_{ii} denote the transition probabilities: the likelihood to remain in the same state.

where $\omega_i > 0$, $\alpha_i^+, \alpha_i^-, \beta_i \geqslant 0$ $(i = 1, 2)$, $\psi > 2$, φ is an scale factor that ensures that the conditional variance remain finite.[2] Beside the estimation of GARCH parameters for each regime, the matrix $\boldsymbol{\pi}$, which contains the transitions probabilities and allows the system to go from one state to the other (see Figure 1), is included in the estimations,

$$\boldsymbol{\pi} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

It is important to remark the qualitative meaning of new coefficients,

- The *news impact* is divided into two coefficients α^+ and α^-, which capture the reaction of the market to different sign innovations. A special case is the *leverage effect*, that occurs when α^- exceeds the magnitude of α^+, indicating that investors reacts more before the presence of bad news.

- Parameter ψ tells the degrees of freedom of Student t distribution. This magnitude captures the weight of the tails of the returns conditional distribution. A smaller value of ψ indicates a heavy-tailed distribution, meaning that the market is prone to big movements of either sign.

- Transition probabilities p_{ii} inform about the likelihood to remain in the same state. Therefore, closer values to 1 make mixing states more difficult.

The proposed Asymmetric MS-GARCH captures asymmetry of the market, explains the likelihood of investors of going from one state to another

[2] For a complete description of the model see Ardia (2008).

and calculates the level of kurtosis of returns distribution. Therefore, it allows us to to analyze the performance and the volatility of Chinese stock markets, as it enables us to understand better the investors behaviour.

4. Data and Results

To analyse Chinese stock markets we use daily data of Shanghai, both A and B, from October 25, 1992 to December 18, 2012, so the sample size is 5010. Data is divided in four different periods according to the more relevant historical changes for each market (see Table 1). The complex nature of the model proposed in Section 3 has lead us to use an alternative solver to perform the estimations. Specifically, we have use the **DEoptim** package (Ardia et al., 2015), which has a very robust performance in the specified framework, as ensures convergence towards the global optimum (Mullen et al., 2011). In order to reach parameters convergence, we have a long run in the DEoptim solver, where the maximum number of iterations is 3000 and population is set to 200. Calculations have been carried with **R** 3.3.0.

	Market A		Market B	
	Beginning	End	Beginning	End
Period A	1992/10/25	1997/05/9	1992/10/25	1997/05/9
Period B	1997/05/12	2003/07/8	1997/05/12	2001/2/18
Period C	2003/07/9	2008/08/31	2001/2/19	2008/08/31
Period D	2008/09/1	2012/12/18	2008/09/1	2012/12/18

Table 1: **Analyzed time frames for Shanghai A and B markets.**

Results for Market A

The Table 2 shows the estimations results for Market A. Note that, initially (P_A), the Chinese domestic market suffers several turbulences, which is somehow expected as it is an unexplored field for national investors. Many parameters reveal a changing market: both regimes do display a leverage effect ($\alpha^- > \alpha^+$), and the low value of p_{11} makes the system moves towards the high volatility regime, where investors react to innovations of negative signs more violently than in regime 1. This fact, together with the low magnitude of β_2, reflects a market that is over-reacting to news, which makes the volatility explosive (as stated by Haas et al., 2004). The near three degrees of freedom of the conditional distribution (ψ) shows the heavy tails

	ω	α^+	α^-	β	p_{ii}	ψ	σ_y
P_A - Low	9.087e-15	0.1101	0.1985	2.205e-06	0.63471	3.024	0.02058
P_A - High	2.462e-04	0.5321	0.6953	3.682e-01	0.98503		
P_B - Low	0.00000	0.00003	0.00413	0.00241	0.79088	2.00830	0.13923
P_B - High	0.01679	0.93651	0.94067	0.06090	0.97950		
P_C - Low	0.00001	0.06233	0.06686	0.89470	0.99912	4.51052	0.01293
P_C - High	0.00008	0.00000	0.21723	0.77835	0.99980		
P_D - Low	0.00005	0.00000	0.08894	0.65679	0.99812	4.41525	0.01546
P_D - High	0.00075	0.06764	0.01491	0.02309	0.98526		

Table 2: Asymmetric Markov-Switching GARCH for Shanghai A for the given periods.

of the Market A. Therefore, big "surprises" of both signs, either positive or negative, are likely to happen. Indeed, these parameters reveal a challenging investment scenario, i.e., a market where big changes often occur, and investors are ultra sensitive to news. Facts that may be an evidence of investor's learning process about how to manage available information in a recently created market.

The uncertainty of the market becomes even greater in the period P_B. After the first legal reformations of the Market A, besides the arrival of the Asian crisis, high volatility regime clearly continues dominating the system. High volatility regime for this period exhibits remarkable values for news impact (α^+ and α^- reach values greater than 0.93) though leverage effect is very small, fact that leaves β_2 with a reduce magnitude. Consequently, national investors increase their sensitivity to news again. The degrees of freedom of 2.0083 implies that big innovations of both sign more likely to happen, raising the likelihood of having extreme market movements. Furthermore, the great value of σ_y (0.13923 in P_B vs 0.01950 during P_A) also supports the high volatility of this period. Therefore, even the government repeatedly changed the stamp tax during this period trying to make the market less unstable, it failed to achieve the target, as stated by unconditional volatility, news impact and heavier tails.

The period P_C reverses the volatility structure of the Market A. Ten years have elapsed since resuming the operation of the market: individuals have learned to manage better the available information, investors who probably input a huge amount of speculative capital are reduced and the government has engaged the QFII program. For this period, the p_{ii} values indicate that mixing regimes is infrequent, and the low volatility regime estimated coefficients resemble to the ones usually observed in developed markets, as news impact is below 0.1 and decay parameter is under 0.9. We also find out greater degrees of freedom and the unconditional volatility decreases dramatically, which reflect a more stable market where extreme movements are more controlled and investors display a more calm behaviour to market innovations. Therefore, this magnitudes support evidence that the regulatory effort of the government together with more experienced investors stabilise the market performance.

Finally, P_D starts with the 2008 global crisis, so volatility behaves similarly to former period. Transition probabilities remain closer to one, making mixing very unlikely. The weight of tails of the conditional distribution decreases slightly compared to P_C, fact that supports that the market is finally stabilising. Note that the leverage effect arises again in low volatility regime. Hence, there is evidence that Market A is not receiving the negative consequences of the global crisis. One possible explanation might be that Market A is developing peacefully because Market B is suffering the effects of the extremely turbulent financial situation.

Results for Market B

The Table 3 shows the estimations results for Market B.

	ω	α^+	α^-	β	p_{ii}	ψ	σ_y
P_A - Low	0.00005	0.99921	0.48945	0.25401	0.99094	2.96219	0.05508
P_A - High	0.00023	0.59603	0.94105	0.22707	0.98973		
P_B - Low	0.00001	0.00112	0.00000	0.00232	0.72598	2.00931	0.20702
P_B - High	0.03476	0.38536	0.62125	0.38985	0.97611		
P_C - Low	0.00048	0.00000	0.00037	0.00002	0.77777	2.00295	0.23193
P_C - High	0.04471	0.50035	0.51665	0.46855	0.98295		
P_D - Low	0.00008	0.00277	0.30136	0.10315	0.51605	3.42928	0.06000
P_D - High	0.00002	0.03983	0.18550	0.83280	0.92918		

Table 3: Asymmetric Markov-Switching GARCH for Shanghai B for the given periods.

The opening of the Market B attracts foreign investors' attention, and the P_A period provides some interesting features about how they performed in the market. Firstly, regimes 1 and 2 are present, though mixing is infrequent. Secondly, low values of β_i exhibit a market that quickly forgets the past conditional variance, i.e., shocks in the market remain only for a briefly period of time. Related to the news impact structure of both regimes, note that, on the one hand, for low volatility regime, international investors react in a very optimistic way (α_1^+ nearly doubles α_i^-); on the other hand, this dynamics is totally reversed for high volatility regime, with a strong leverage effect. Finally, the returns conditional distribution displays heavy tails, but lighter than Market A for the same period. Therefore, the estimations show that Market B starts its path more peacefully than its national counterpart.

A different scenario is reflected in P_B period, where the system tends to move to higher volatility regime. Dynamics of $h_{t,2}$ features a remarkable leverage effect and a reduced value of β_2, indicating that investors are over-reacting to bad news (during P_A they were over-reacting to good news). Furthermore, ψ reduces, therefore big movements are expected, and unconditional volatility, σ_y, increases (four times greater than in P_A). The change for this period might be explained by two facts: the initial illusion of international investors is fading away, and Market B have not still learnt enough about how to manage the available information. We also must add the effects of the Asian crisis of this period.

In P_C the situation of market is not better off, since transition probabilities are similar to the ones estimated for P_B. Indeed, coefficients for low volatility regime are almost negligible. Thus, high volatility regime governs the dynamics of the system. The most noticeable change of the fitted coefficients is that the leverage effect has almost disappeared, but still remains present. Unconditional volatility and degrees of freedom show nearly the same values than in P_B. The fact that the government allowed Chinese nationals holding foreign currency, fact which led to international investor to withdraw capital, together with the likely inertia of some side effects remaining from the Asian crisis, may explain the results for this period.

Analysing P_D reinforces the strength of high volatility regime in Market B, as p_{11} diminishes again. News impact coefficients in state 2 feature again a severe leverage effect, together with the increasing of β_2 (0.83280). The interpretation of this magnitudes led the market to a difficult scenario, a situation where bad news seriously affects volatility, and now, thanks to a higher decay parameter, shocks in the market slowly disappears. On the positive side we highlight higher degrees of freedom and a reduction of σ_y respect to P_C (although the volatility structure displays hard times).

5. Final remarks

The current approach provides evidences about the opposite directions followed by the two Chinese stock markets. Specifically, the only feature that both markets has commonly is the presence of really heavy tails. In fact, while Market A becomes more mature and unconditional volatility decreases, Market B evolves towards to high volatility regimes, which, complemented with the reduced number of firms in this market, shakes the performance of the market.

Regarding legal reforms, on the one hand, the initial attempts of controlling the Market A by changing transaction costs had no positive effect. Nonetheless, the second major legal reform in Market A, the QFII, might contribute to reduce the market uncertainty. On the other hand, Market B is less fortunate in this matter: allowing Chinese nationals holding foreign currency to operate in the market did not improve the situation. Indeed, the volatility structure displayed a violent behaviour. Therefore, Market B does not achieve the maturity of Market A.

Concerning to influence of sentiments in the markets, in Market A news impact provides evidence of it during the first 10 years, after this point the situation is reversed, although leverage effect does not disappear. Contrarily, Market B behaviour is explosive to news, and the uncertainty structure does not change significantly as time evolves.

To sum up, we may characterise Chinese stock markets as a not for faint-hearted investors: highly asymmetric regarding news, prone to overreact to bad news, easy to reach high volatility regimes and with a large amount of big movements of either sign.

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