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Article

Interaction between Industrial Policy and Stock Price Volatility: Evidence from China's Power Market Reform

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Abstract: China combines green energy and industrial policy in its power market reform with various policy initiatives, including price support scheme for electricity from renewable sources and subsidies in the push for broader use of greener energy. This study focuses on the impacts of power market reform on the stock price volatility of listed power companies: 1) we use the Iterative Cumulative Sums of Squares (ICSS) algorithm to identify structural break points in stock prices; 2) we analyze the characteristics of stock price volatility based on the GARCH model; 3) we report the impact of power regulation on stock price fluctuations based on the Autoregressive Distributed Lag (ARDL) model. The result suggests three structural breaks in China's power stock price volatility were related to the promulgation of power market reform policies. We find that industrial policies promote the reduction of power stock price fluctuations and its impact on power stock price volatility is consistent in the long run. However, our study also indicates the recent policies related to renewable energy do not have a very significant impact on the power stock market.

Keywords: Industrial policy; Stock price volatility; China's Power market

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1. Introduction

When considering the link between investments and policy in China's power market, it is important to note that China's energy regulators have been characterized by overlapping jurisdictions. China's electricity sector consists of a mix of state and local owned enterprises. The last major structural change occurred in 2002 with the dismantling of the State Power Corporation, resulting in competition in power generation and openness in energy investment. The government required certain generators to participate in the markets, forcing them to compete against one another for operating hours in the form of annual, or sometimes monthly, contracts with end-users or retailers. However, market concentration remains high with the top five companies accounting for about 50% of the market and the whole energy industry is still policy-oriented, which provides golden opportunity to observe policy implications for industrial development through stock market.

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China started to combine green energy and industrial policy in its power market reform in 2001, signaled by the Tenth Five-Year Plan for New and Renewable Energy Commercialization Development, which includes price support scheme for electricity from renewable sources and subsidies in the push for broader use of greener energy. Total power consumption in China has grown rapidly, especially from 2002 to 2011 during which the average growth rate of power consumption was more than 10%.[1] As air pollution caused by "PM 2.5", or fine particulate matter has become a social problem, curbs on coal use as well as expansion of clean energy use are recognized as urgent tasks. China also set the goal of peaking its CO_2 emissions around 2030 in the "Paris Agreement", which took effect in November 2016. In this agreement, China's energy policy is responding to these changes in domestic and international circumstances, and therefore, continued political stress are imposed to reduce CO_2 emissions.

In a world with a steadily rising demand for power generation, policies about power generation and consumption are likely to have a key bearing on the financial markets. Meanwhile, sudden structural breaks could affect the dynamics of stock prices. This study aims to investigate the interdependence between China's stock market and the China's power market during 2006-2012 (a substantial slowdown in the increase of primary energy consumption since 2012, with year-on-year increase remaining at 1.0 % in 2015, and 1.4% in 2016), with careful consideration paid to the possibility of structural shifts in the mean and variance processes. We identify the impact of China's power market reform on listed power companies' performances and capacities to attract investment and explore what kind of reforms would be more suitable for China's power industry development. Therefore, in the following studies, we would address two significant issues: characteristics of stock price volatility of the listed power companies with considering structure breaks; and the impact of power industrial policy reform on stock price volatility.

This paper proceeds as follows. Section 2 reviews the main studies and results regarding structure breaks in the process of stock price fluctuation, and the factors affecting stock price volatility. In the next section we discussed the data used as well as variable selection. Section 4 introduces methodologies, including: (1) the iterative cumulative sums of squares (ICSS) method for determining the structure break of stock price volatility; (2) generalized autoregressive conditional heteroskedastic (GARCH) model for analyzing the characteristics of stock price volatility; and (3) autoregressive distributed Lag（ARDL）model for studying the impact of power industrial policy reform on stock price volatility. Our results and analysis are presented in the fifth section with conclusion and policy implication in the last two sections.

2. Literature Review

Structural break in stock price fluctuation is an actively researched topic. Many studies have attempted to identify the most important event that precipitates structural breaks, such as macroeconomic events, reform policies, and crisis events. The macroeconomic situation is considered to be the most important factor by many scholars. For example, Chihoun and Mi-Ok found that firms with SEO have sustainable development in operational structural change[4]; Fama argued that capital expenses, industrial production, gross national product

[1] China's Power Industry Statistical Compilation (2014)

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(GNP), money supply, inflation and interest rates have a strong positive influence on stock price fluctuations[5]. By using the cumulative sums of squares (ICSS) algorithm, Hammoudeh and Li studied the characteristics of stock market volatility in the Arabian Gulf region, they found that structural changes were usually caused by the impact of international events, for instance, the Asian Financial Crisis and the 9·11 terrorist attacks. They suggested that international events are the major origins of structural changes[6]. Wang and Tomoe tested stock returns data from 1994 to 2006 of five new European Union (EU) members and argued that reform in emerging stock markets, exchange rate policies and the financial crisis led to volatility. They also pointed out that many previous studies did not consider the structure of the volatility, which resulted in overestimating volatility[7]. Babikir et al. measured the Johannesburg Stock Exchange All Share Index and found that structural breaks mainly stem from international financial crises; they argued that the presence of a structural break point should be considered in forecasting stock market volatility, especially in the long term[8].

Significant attentions have been paid to the characteristics of fluctuations in China's stock prices and the influential factors. Chen and Huang (2002) illustrated that asymmetry features existed in fluctuations in China's stock market, meaning that the impact of negative information on stock price fluctuation is greater than that of positive information[9]. Wang and Zhang indicated that China's stock market has a long memory in nature, which means that some unexpected events have a long-lag influence on stock price fluctuations and current risks will affect future risks continuously[10]. There are different opinions about whether there are various characteristics across different stages in China's stock market. Song and Jiang suggested that China′ s stock market volatility has poor stability, and the stratification of stock price volatility is hard to distinguish[11]. Schwert related stock market volatility to the time-varying volatility of a variety of macroeconomic variables, including money growth, industrial production growth, and other measures of economic activity[12]. Wang and Gao concluded that there are weak correlations among the Chinese stock market, inflation, money supply and stock price volatility[13]. Moreover, Wen et al. argued that there is a relationship between oil prices, economic growth, money supply, inflation and Chinese stock market volatility by using data from 2002 to 2010 based on the multi-factor EGARCH (1, 1)-M model[14]. While Dong and Wang found a negative relationship between stock market volatility and economic growth in China by using data from 1993 to 2007 based on the Wavelet Transform method[15]. Beltratti illustrated that the stock price volatility of the S&P500 is affected by the volatility of economic and policy variables, and a positive relationship exists between economic growth and price volatility. Of particular interest[16]. Li and Fu studied factors affecting China's power stock price and found that coal prices had a significant impact on power stock price fluctuations, since thermal power is the largest share of the power industry in China[17]. Zhao (2016) studied the impact of financial crisis on electricity demand in north China, they found the electricity consumption, which affected stock value of electric enterprises, and economic growth are highly correlated[18].

In a related literature on the interpretations of structural change in stock price volatility , Leahy and Whited (1996）Bloom et al (2007), Baum et al(2008) and Panousi and Papanikolaou (2012) argue that the stock price volatility represents the uncertainty faced by the individual firm. Leahy and Whited (1996) [43] find between investment negatively correlated to the firm's daily stock volatility for U.S. manufacturing firms during 1981–1987. Bloom et al. (2007)[46]

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establishes a model to show firms reduces long-term investment through shocks to expected sales channel. Baum et al.(2008)[44] and Bloom et al.(2007)[46] report similar results for U.S. manufacturing firms during 1984–2003 and for UK firms from 1972 to 1991, respectively. Baum et al. (2010)[45]distinguish between own uncertainty, based on a firms' stock returns, market uncertainty, derived from stock index returns, and a measure of covariance between the two. An increase in market uncertainty inhibits firm-level investment, and the sign of the effect of the other measures of uncertainty on firm-level investment depend on interaction with cash flow.

In summary, although there are significant literature on stock price volatility and its influencing factors, a few of them studied the stock price fluctuations of power companies (Li and Fu[17]); Also, studies on the characteristics of China's power stock price volatility that consider structural breaks and the impact of power regulation on price volatility are scarce. The contributions of this paper are twofold: First, our analysis is one of the few studies that examine the stock price volatility characteristics of listed power companies in China. Second, we address the relationship between China's power market reform and the stock price volatility.

3. Materials and Methods

3.1. Data collection and variable selection

The data used in this study can be categorized into two groups: one is the data for determining the structure breaks of stock price volatility and analyzing the characteristics of stock price volatility; these data are based on daily information. The other group is the data for exploring the impact of power industrial policy on power stock price volatility; these data are based on monthly information, since macroeconomic variables will be considered, and these kinds of macroeconomic data only can be obtained at the monthly level.

The first group of data refers to the power stock price index (PSPI), and the Shanghai A-share Composite Index (SHCI), which are collected from the Great Wisdom market software. The sample contains 61 listed power companies in China, whose operation fields include thermal power, hydropower, waste heat generation, and so on. The market capitalization of China's listed power companies is more than 480 billion Yuan, accounting for 3.1 % of the total market capitalization in the SHSE and SZSE[2].We selected August 30, 2006 to November 15, 2012 as our study period, since the PSPI was released beginning from August 30, 2006. Both the samples of PSPI and SHCI are 1,551. The second group of data contains 75 samples from August 2006 to October 2012.

The explained variable in this study is: Power stock price change (PS), which is measured by the stock price index of 61 China's listed power companies (CLPC) in SHSE and SZSE. We chose the data of the power stock price index at the end date of each month as monthly data. .In this study, we took the August 2006 as the base (i.e. month 0). Power stock price is converted to constant price using Consumer Price Index at month level.

The explanatory variable in this study is power industrial policy, which is referred to as the policy that caused the structure break of power stock price volatility to occur. Jin and Tang

[2] According to China Securities Regulatory Commission (CSRC): Industry Classification Results of Listed Companies (2th Quarter, 2013) and Great Wisdom market software.

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claimed that policy factor is the primary reason for market movements in the period from 1992 to 2000 in China[19]. Malik suggested that events, policies or other kinds of events need to be considered in process of estimating the volatility of the CLPC stock price[20]. Because we pay more attention to the impact of power industrial policy on the volatility of power stock price, in this study the explanatory variable only refers to power industrial policies rather than other kinds of events.

The control variables are: (1) Coal price (CP). Thermal power is the most important power in China, meaning a large proportion of costs in the power industry are from fuel consumption, and coal price largely affects the CLPC financial situation and stock price volatility. We used the Datong mixed coal prices from the Fenghuang Finance Web site (http://finance.ifeng.com/) to capture the coal price. Coal price was converted to constant price based on August 2006, using the Producer Price Index at the monthly level. (2) Power generation (PG). Power generation is an important indicator reflecting GDP growth; meanwhile, it has an important impact on power companies' profits (China's on-grid tariff is fixed; power companies' profits depend largely on the amount of power generation). Power generation data were collected from the Hexun Data Center (http://mac.hexun.com/) (3) Fund supply (FS) on the stock market, which is captured by the supply gap between money M1 and M2. The reason is that the scope of M1 includes cash and call deposit whileM2 includes cash, call deposit and fixed deposit, the supply difference between money M1 and M2 can represent the fund used to invest in the stock market. The data of M1 and M2 were collected from website of the People's Bank of China[3].

3.2. Research Methodology

3.2.1. Iterative Cumulative Sums of Squares (ICSS) method

The ICSS algorithm is used to determine the structure breaks of stock price volatility caused by a policy or other significant events. Structural break means a sudden change at an unknown point in the finance time series. The ICSS algorithm is an effective model to test the possibility of structural breaks and to identify the particular time of structural breaks, which was introduced by Inclán and Tiao[21]. In this method, it is assumed that the series that we consider presents stationary behavior for some time, and then the variability of error term changes suddenly. It will not change for some time at the new value until another change occurs. Based on the above assumption, Inclán and Tiao [21] defined the following formula:

$$IT = \sup_k \left| \sqrt{T/2} D_k \right| \tag{1}$$

Where, IT represents the structure breaks of stock price volatility.

$$D_k = C_k / C_T - k/T, \quad k = 1, 2, 3 \cdots T \tag{2}$$

Where, C_k is the cumulative sum of the squared observation, which is introduced to estimate the change number and the point in time of change. It is expressed as:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \ \ k = 1,2,3,\ldots,T \tag{3}$$

[3] Data source: http://www.pbc.gov.cn/

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Where, ε_t is distributed with 0 mean and variance δ_t^2.

$$\varepsilon_t = r_t - \mu \tag{4}$$

Where, r_t is the returns on a stock index from time t - 1 to t, $t = 1, 2, 3 \ldots, T$. μ is the constant (conditional and unconditional) mean of p_t.

$$r_t = 100 \times \ln(p_t / p_{t-1}) \tag{5}$$

Where, p_t denotes the value of the stock index at time t.

There are sudden changes in the series when the statistic values drift up or down from the threshold, which define the upper and lower bounds for the drifts. The value of the threshold D* is estimated from 10,000 replicates of series of T independent N(0, I) observations for the desired p = .95, following the same procedure introduced by Inclán and Tiao [21]. If the value of IT is bigger than a threshold given, the null hypothesis is rejected, and the value of k^* is taken as the break date with high probability. Otherwise, the null hypothesis is accepted, indicating that there is no obvious break point.

3.2.2. Generalized Autoregressive Conditional Heteroskedastic (GARCH) model

Volatility is a very important indicator in economic and financial research, and the GARCH model is widely used in volatility analysis of portfolios, asset pricing and risk management. Predicting the one-period forecast variance based on recent past variances, Engel proposed the Autoregressive Conditional Heteroskedastic (ARCH) model to calculate the volatility of time series[22]. His student, Bollerslev, extended it to embrace more past information; hence, a more concise expression exists in a GARCH model, which hereafter became one of the main volatility models for time series[23]. Hansen and Lunde (2005)[39] argued that GARCH (1, 1) works quite well in estimating volatility of financial returns as compared to more complicated models. In estimating the GARCH model, we examine different kinds of commonly used combinations of (p,q) in the stock market according to the two most commonly used model selection criteria, the Akaike information criterion and the Schwartz Bayesian criterion, and the underlying assumption of the GARCH model. Of the potential and most commonly used GARCH models for measuring stock market volatility, GARCH(1,1) is valid and presents satisfying interpretation. Therefore, we use GARCH(1,1) to measure volatility.

The GARCH (1, 1)[4] model can be expressed below:

$$y_t = \varphi x_t + \varepsilon_t, \varepsilon_t \sim N(0, h_t) \tag{6}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \omega > 0, \alpha > 0, \beta > 0, \alpha + \beta < 1 \tag{7}$$

[4] The GARCH model has been described typically as the GARCH (1,1) model. It is widely used in studying volatility issues. More discussion can be obtained from Robert Engle (2001).

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Where, y_t is the dependent variable, x_t is the explanatory variable, ε_t is distributed with mean 0 and unit variance, h_t represents the conditional volatility of y_t, ω is a constant item, $\alpha+\beta$ indicates the persistence of the GARCH (1,1) model. Considering the structure change points identified in the variance, the GARCH model is estimated in different sub-samples with sudden changes displaying the persistence of volatility.

3.2.3. Autoregressive Distributed Lag（ARDL）model

On the basis of analyzing the characteristics of power stock price volatility, we intend to find how power industrial policy affects stock price volatility. As aforementioned, we argued that the factors affecting the volatility of power stock prices include power industrial policy, power generation, coal price, and money supply. The model for analyzing the impact of power industrial policy on power price volatility, using the natural logarithm of all variables except the dummy variables of power industrial policy, is as follows:

$$\ln PS_t = \alpha_0 + \alpha_1 \ln PG_t + \alpha_2 \ln CP_t + \alpha_3 \ln FS_t + \sum_{i=4}^{7} \alpha_i D_i + \gamma_t \tag{8}$$

Where, PS_t is power stock price return, or power stock price volatility change at time t; PG_t is power generation, CP_t is coal price, and FS_t indicates fund supply on the stock market. D_i is the dummy variable representing power industrial policy that is of most interest. The subscript i represents the policy that brings about the ith time of structure break of the power stock price.

To examine the relationship between explanatory variables and the explained variable in the long-term and dynamic change in short-term, we introduced the Bound Co-integration Test developed by Pesaran et al.[24], which is also called the ARDL model. Compared with other single co-integration tests, this method has two advantages: First, under the condition that the variables are I (0) or I (1), a co-integration test can be carried out regardless of whether a same order integration relationship exists between variables; second, it is more suitable for small samples that range from 30 to 80 because of the smaller requirements for sample size in the model estimates. The sample size in this study was small, with only 75 observations. For this reason, it is appropriate for using the method. The ARDL model of Eq. (8) is as follows:

$$\begin{aligned}\Delta \ln PS_t = {} & \delta_0 + \delta_1 \ln PS_{t-1} + \delta_2 \ln PG_{t-1} + \delta_3 \ln CP_{t-1} + \delta_4 \ln FS_{t-1} + \sum_{i=5}^{8} \delta_i D_i + \sum_{i=1}^{4} b_i \Delta \ln PS_{t-i} + \\ & \sum_{i=1}^{4} c_i \Delta \ln PG_{t-i} + \sum_{i=1}^{4} d_i \Delta \ln CP_{t-i} + \sum_{i=1}^{4} e_i \Delta \ln FS_{t-i} + \sum_{i=1}^{4} f_i \Delta D_i + \phi_t\end{aligned} \tag{9}$$

Where, Δ means difference，for instance $\Delta lnPS_t = lnPS_t - lnPS_{t-1}$

The bounds test is based on the *F*-test or *Wald* statistics, and it is the first step in the ARDL approach. Accordingly, the null hypothesis of Eq. (5) is that there is no level relationship that

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exists across variables for the long-term period. That means:

Null hypothesis: $H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 \ldots = \delta_8 = 0$;

Alternative hypothesis: $H_1: \delta_1 \neq 0$, or $\delta_2 \neq 0$, or …… $\delta_8 \neq 0$

The above hypotheses are judged by *F*-statistics of joint significance of δ_1, δ_2, δ_3, δ_4, … δ_8, and the critical value can be obtained. If the estimates of *F*-statistics are more than the upper bound of the thresholds, the presence is indicated of a co-integration relationship between variables in the long-term; if the *F*-statistics are less than the lower bound of the thresholds, there is no long-term co-integration relationship between variables; if the *F*-statistics are between the upper and lower bounds of the thresholds, whether the long-term co-integration relationship exists between the variables is unknown.

Co-integration is used to identify whether there is a long-term equilibrium relationship between multi-economic variables. The Error Correction Model (ECM) is used to identify the balance between the long-term statistical relationship, and the short-term dynamic relationship.

$$\Delta \ln PS_t = \mu + \sum_{i=1}^{4} b_i \Delta \ln PS_{t-i} + \sum_{i=1}^{4} c_i \Delta \ln PG_{t-i} + \sum_{i=1}^{4} d_i \Delta \ln CP_{t-i} + \sum_{i=1}^{4} e_i \Delta \ln FS_{t-i} + \sum_{i=1}^{4} f_i \Delta D_i + \lambda ecm_{t-1} + \varepsilon_t \tag{10}$$

Eq. (10) reflects the dynamic relationship between variables and CLPC return in the short-term.

Since causality tests are sensitive to the stationarity of the series, we first study the stationarity properties of the variables on the basis of a unit root test. Unit root testing is used to study the stationarity properties of variables, and it is an essential tool to test the order of integration. In the case where the order is beyond one, the ARDL method becomes invalid. There are a variety of unit root tests, such as augmented Dickey–Fuller (ADF) (Dickey and Fuller[25]), Elliot–Rothenberg–Stock Dickey–Fuller GLS de-trended (DF-GLS) (Elliot et al., [26]), and Phillips–Perron (PP) (Phillips and Perron[27]), among which the ADF test is generally used when there is a small sample volume (Schwert[28]) Several studies including Perron (1997) [39]and Lumsdaine and Papell (1998)[40], has shown that bias in the usual ADF unit root tests is small after endogenously determining the time of structural breaks. Perron (1997, pp. 356)[39], argues that "if one can still reject the unit root hypothesis under such a scenario it must be the case it would be rejected under a under a less stringent assumption". The results of the unit root test are shown in Table 1. Table 1 shows that power stock price (PS) and power generation (PG) are I(0) , while I(1) for coal price (CP) and fund supply on the stock market (FS), indicating the suitability of an ARDL model.

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Table 1 Results of ADF unit root test

variables	Original ADF statistics	Original Type (c,t,k)	Original P-value	First difference ADF statistics	First difference Type (c,t,k)	First difference P-value
PS	-4.821	(c,0,5)	0.000			
PG	-5.183	(c,t,0)	0.000			
CP	2.689	(c,0,1)	0.244	6.668	（c,0,0）	0.000
FS	-2.503	(c,t,0)	0.326	-7.511	(c,t,0)	0.000

Notes: All variables (monthly data) are in logarithmic form, type (c, t, k) represents intercept, trend, lag order; it is marked 0 if the item is not included.

The original ADF of PS and PG is statistically significant at 1%; hence the first difference results are not provided. According to Rushdi et al.[28], the original value of PS, PG and the first difference value of CP and FS can be calculated together.

4. Results and discussions

4.1 Structural breaks of stock price fluctuation

To better illustrate the characteristics of the fluctuation of the Power Stock Price Index (PSPI), we also analyzed structural breaks of the general stock price (Shanghai A-share Composite index: SHCI) and compared the structural break differences between these two stock prices. Results of these structural breaks for PSPI are shown in Fig. 1. Results of the structural breaks for SHCI are shown in Fig. 2. Fig. 1 indicates the structure break dates for PSPI are 2007/5/29, 2008/2/1, 2009/10/13, and 2012/1/18 respectively, which divides the whole sample into five sub-samples. Fig. 2 indicates the structure break dates for SHCI are 2006/12/22, 2008/1/18, 2008/11/19, 2009/9/9, and 2011/1/21 respectively, which divides the whole sample into six sub-samples. Based on these results of Fig. 1 and Fig. 2, a few important findings are as follows.

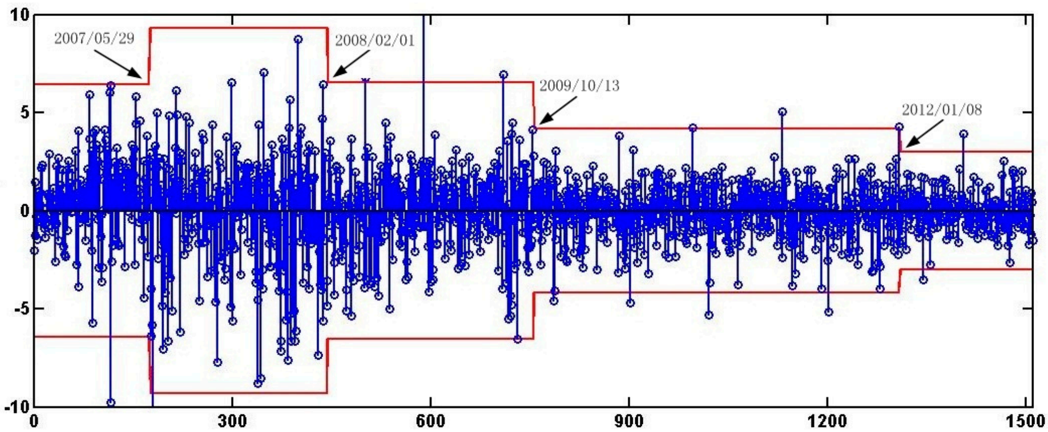

Fig.1 The Power Index (PI) and ± 3 standard deviation bands

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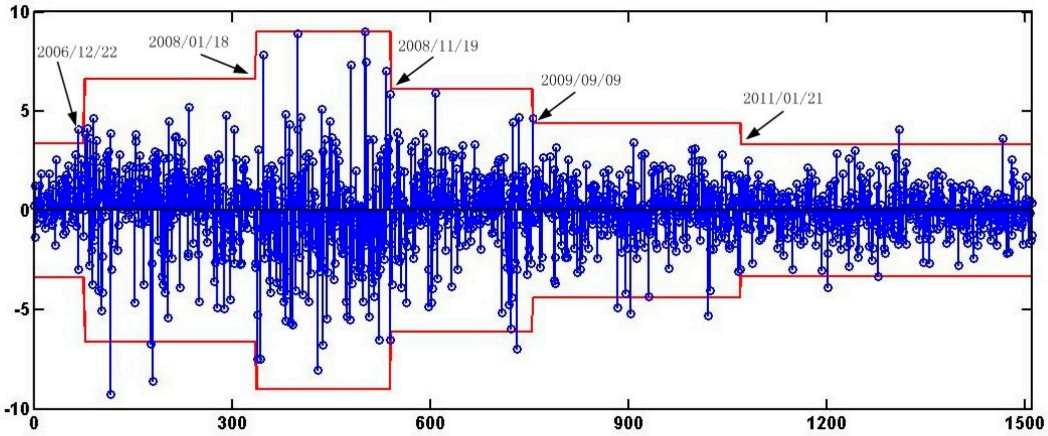

Fig.2 Shanghai Composite Index (SHCI) and ± 3 standard deviation bands

First, regarding frequency of structural breaks, we found that frequency of structural breaks differs between the PSPI (four times) and SHCI (five times), which implies that China's stock market has better stability in the PSPI than the SHCI. It also implies that the PSPI is exposed to volatility related to industry events or policy announcements apart from the common elements affecting the general stock market.

Second, from the time perspective of structural breaks, we found that a large difference exists between the PSPI and the SHCI, which means that events in the power industry have a greater impact on fluctuations in the PSPI compared with the macroeconomic environment. The specific date of break points identified by the ICSS algorithm and the corresponding power industrial policies are shown in Table 2.

Table 2 Structure breaks of China's power stock price and corresponding policies

Change points	Date	Events
1	May 29, 2007	*Measures of Price and Facility Operation of Desulphurization for Coal-fired Power Units* promulgated by the National Development and Reform Commission (NDRC) on May 29, 2007.
2	February 1, 2008	*Restriction on Employees Increasing Their Share in Power Generation Firms* promulgated by State-owned Assets Supervision and Administration Commission of State council, etc. on January 28, 2008.
3	October 13, 2009	*Notice on the Regulation of Energy Trading Price* promulgated by NDRC and the State Electricity Regulatory Commission (SERC) on October 11, 2009.
4	January 08, 2012	*Drawing the Roadmap for Deepened Reform for Power Development in the Twelfth Five-Year Plan Period* promulgated by the SERC on January 08, 2012.

Source: China Yearbook of Electric Power (2006-2012) and China Electric Power Information, http://www.cpnn.com.cn/.

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Table 2 shows that at the first break point on May 29, 2007, the document of *Management of Tariff and Facilities of Desulphurization for Coal-fired Power Units* was issued, which implied the operational cost of power generation would increase and the risk of investment in power stock market would increase. As such, the fluctuation of the PSPI increased. At the second break point on February 1, 2008, a policy restricting employees from increasing their share in power generation enterprises was issued. This policy would reduce the flow of funds into the CLPC; hence, the fluctuation of the PSPI took a downward trend. The third break of the PSPI took place on October 13, 2009, when the National Development and Reform Commission and State Electricity Regulatory Commission regulated the power trading price. The policy stipulated that the on-grid power price within a province must be consistent with the standard power price of the province; however, power trading prices across provinces or regions have relative flexibility. The last structure break point is on October 13, 2009, when the State Electricity Regulatory Commission (SERC) issued the document, *Drawing the Roadmap for Deepened Reform for Power Development in the Twelfth Five-Year Plan Period*. This document stipulates that the industry's transmission and distribution businesses will be separated into two parts, and large power consumers will be permitted to purchase power directly from power generators; meanwhile, the market will decide the power price. The third and fourth power regulations in Table 2 provided the signal that China's power market would move in a more orderly and standardized direction, thus decreasing the anticipated risk of investment in this market. Accordingly, the fluctuation of the PSPI decreased.

In addition to the four power regulation policies presented in Table 2, there are some other important power regulation policies (shown in Table 3) were issued over this study period, . Distinct from the policies in Table 2, those in Table 3 do not contribute to the structural breaks in China's power stock price. Of the six policies in Table 3, three relate to renewable energy development. Currently, the proportion of renewable energy generation contributes only about 2 % of the total power. As such, the policies related to renewable energy do not have a very significant impact on the power stock market.

Table 3 Key power regulation policies issued from August 30, 2006, to November 15, 2012

	Date	Policies
1	November 13, 2006	*Notice on Promoting the Development of Wind Power Industry* issued by the National Development & Reform Commission (NDRC) and the Finance Ministry.
2	January 20, 2007	*Notice on Speeding up the Work of Shutting Down Small Thermal Power Units* issued by NDRC.
3	June 19, 2008	*Temporary Price Intervention of Coal Used by Power Generation Units* issued by NDRC, which provided the highest settlement price of coal.
4	July 20, 2009	*Notice on Improving Wind Power Price* issued by NDRC, which established the benchmark price for different wind power resources.
5	July 24, 2011	*Notice on Improving Solar Photovoltaic Price* issued by NDRC, which established the benchmark price for solar photovoltaic.
6	June 18, 2012	*Proposals on Encouraging and Guiding Private Capital Flowing into Energy Fields* issued by the National Energy Board.

One of these six policies calls for shutting down small thermal power units. This measure can improve the operational efficiency of power generators; on the other hand, the work itself will increase operational costs in the short run. Hence, it does not have an important impact on power stock price fluctuation.

The policy of price intervention of coal used by power generation units should have an important effect on power stock price fluctuation. However, because it is only a "temporary" price intervention, the effect is not statistically significant.

The most recent policy issued by the National Energy Board on June 18, 2012, is the *Proposals on Encouraging and Guiding Private Capital Flowing into Energy Fields*. This document stipulated that private investment in energy sectors, such as in power plant construction and industrial upgrading fields, was stimulated. It is beyond any doubt that the introduction of private investment in power fields will promote China's power industry. However, it is uncertain what impact it will have on China's listed power firms' performance. Hence, this policy has no significant effect on the power stock market.

4.2 Analysis of the fluctuation characteristics of PSPI

4.2.1 Descriptive statistics results

This analysis differs from the previous analysis as the sample is divided into several different sub-samples according to the detected break points obtained by using the ICSS algorithm. Descriptive statistics for different sub-samples are reported in Table 4, which shows that only the mean of the first sub-sample (August 31, 2006, to May 28, 2007) is positive; the others are negative. These results indicate that compared with the period from August 31, 2006, to May 28, 2007, returns on power stock index (or the change of power stock price volatility) decreased from May 28, 2007, to November 15, 2012.

Table 4 also shows that the full sample and all sub-samples are characterized by statistically significant kurtosis (exceeds 3), suggesting that they are leptokurtic, namely demonstrating a fatter tail and a higher peak (the Jarque–Bera test outcome in the sixth column). Meanwhile, the Jarque-Bera result (the sixth column in Table 4) and Ljung–Box Q-statistic result (the seventh column in Table 4) show that series autocorrelations for squared residuals at any reasonable level exist in the first through fourth sub-samples as well as in the full sample, which indicates that the GARCH model is suitable for these samples except the fifth sample.

Table 4 Descriptive statistics of power stock price volatility

sample (size)	mean	SD	Skewness	Kurtosis	Jarque-Bera(5)[1]	L-B (5)[1]
full sample (1510)	0.014	1.887	-0.368	5.839	541.06*	113.01*
sub-sample 1 (175)	0.627	2.137	-0.561	5.982	74.03*	12.393*
sub-sample 2 (171)	-0.058	2.949	-0.849	4.146	29.887*	5.71***
sub-sample 3	-0.069	2.514	-0.063	4.348	31.252*	25.947*

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(409)						
sub-sample 4 (554)	-0.035	1.392	-0.412	4.152	46.312*	8.73***
sub-sample 5 (201)	-0.028	0.995	0.188	4.341	16.243	3.142

[1] "(5)" means five-order lag. *, **, *** denote significance at 1%, 5% and 10% level, respectively.

The largest standard deviation emerges in the second sub-sample (from May 5, 2007, to February 1, 2008), meaning that from May 5, 2007, to February 1, 2008, power stock price volatility is the greatest. This volatility occurred during this period because China's interest rate was adjusted several times; meanwhile, originally non-tradable stocks, such as the stocks owned by state companies, were permitted to be listed and traded.

4.2.2 The fluctuation characteristics of the PSPI

Table 5 reports the results of the fluctuation characteristics of the PSPI based on the GARCH model. In terms of the model estimated with the full-sample, the value of $\alpha+\beta$ is the highest with 0.988. The value of $\alpha+\beta$ in sub-series 1 to 4 reduced by 34%, 22%, 9%, and 24%, respectively compared with the value of the full sample, and the average value decline in sub-samples is 22.75%.

This result shows that power stock price fluctuation persistence stage is reduced typically when considering structural breaks, which is consistent with the conclusions of Kasman[29]. Kasman argued that the value of $\alpha+\beta$ decreased by 29.2% while considering structural breaks. Christopher and William [30], Malik [31], and Rapach and Strauss [32] also stated that with structure breaks, the persistence of a volatility stage will be reduced.

Table 5 Results of GARCH (1, 1) model

sample (size)	coefficients ω	α	β	$\alpha+\beta$	variance
full sample (1510)	0.038*** (0.011) [0.00]	0.059*** (0.007) [0.00]	0.924*** (0.008) [0.00]	0.988	3.561
sub-sample 1 (175)	0.007*** (0.003) [0.00]	0.448*** (0.126) [0.00]	0.201 (0.189) [0.29]	0.648	4.567
sub-sample 2 (171)	0.002* (0.001) [0.08]	0.158* (0.087) [0.08]	0.612*** (0.179) [0.00]	0.77	8.696
sub-sample 3 (409)	0.004*** (0.001)	0.165*** (0.051)	0.732*** (0.069)	0.897	6.320

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	[0.00]	[0.00]	[0.00]		
sub-sample 4 (554)	0.005** (0.003) [0.04]	0.150*** (0.053) [0.00]	0.600*** (0.149) [0.00]	0.750	1.938

Notes: ***, **, *denote significance at the 1%, 5% and 10% levels, respectively. The data in parentheses "( )" is standard deviation; the data in bracket "[ ]" is P-value.

4.3 The impact of power market reform on power stock price volatility

In this section, we first examine the long-term relationship between the variables. We then explore the magnitude of the policy impact on structural changes in the stock volatility. Finally, we examine the policy impact by type.

As previously discussed, to establish a long-term relationship between the variables, an *F*-test should be applied to Eq. (4). The *F*-test results are displayed in Table 6. Table 6 shows F statistics are higher than the Upper Bound value when it includes the dummy variable; and the P value is 0.000, indicating that a level of significant co-integration exists between the explanatory variable and the explained variable, as well as between the control variables and the explained variable.

In search for the optimal length of time for the level variables of coefficients, the lag selection criteria of the Schwarz Bayesian Criterion (SBC) is utilized (Rushdi, et al. [28]), and the order of lags is selected as 0. The results in Table 6 imply that a long-term relationship exists between the variables. Then, to estimate the parameters of Eq. (5), the ARDL co-integration results between power stock price fluctuations and other variables are reported in Table 7.

Table 6 Results of *F*-test for co-integration

Explanatory variables	ARDL-VECM (Lag order)	F-statistics	Lower Bound	Upper Bound	Cointegration (Yes or No)
LPG, LCP, LFS	(0,0,1)	1.484	2.482	3.757	No
LPG, LCP, LFS, D1, D2, D3, D4	(0,0,0,0,0,0,0)	4.141	2.111	3.363	Yes

Notes: The bound critical value bounds are significant at the 5% level.

Table 7 demonstrates that there is long co-integration between the power stock price (PS) and fund supply (FS), power generation (PG) and coal price (CP). The dummy policy variables (except the first one (D1)) have a significant negative impact on China's listed power companies' stock price volatility in the long term. This indicates that China's power industrial policy reduced the volatility of the power stock price in this study's period. Market based regulation is a signal that the power industry will develop toward more orderly operations. Hence, investors have more confidence in the future development of the power industry, and the stability of the power stock market increased. This result is in line with that of Malik[31], who argued that events, such as policy, are important factors affecting the volatility of the CLPC.

Furthermore, we found that the fourth dummy variable—the policy of deepening power market reform promulgated by the SERC—had the greatest impact on volatility. This implies

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that compared with the policy restricting employees' investment behavior and reform of the power trading price, reforms affecting the entire power market have greater influences on the power stock market. This result aligns with our expectations: More important policies have broader influence, and greater impacts will occur.

Table 7 ARDL long-run co-integration results

Variables	Coefficient	SD	T-statistics	P-value
LPG	-1.808**	0.885	-2.043	[0.05]
LCP	-1.131***	0.682	-1.659	[0.00]
LFS	2.486*	0.792	3.140	[0.10]
D1	-0.105	0.391	-0.267	[0.79]
D2	-0.867**	0.425	-2.039	[0.05]
D3	-1.115***	0.442	-2.521	[0.01]
D4	-1.451***	0.488	-2.974	[0.00]

***, **, *denote significance at the 1%, 5% and 10% levels, respectively.

The co-integration between the control variables, power generation, coal price and stock price is statistically significant, meaning that they have a considerable impact on the power stock market. The negative correlation between power generation (PG) and power stock price indicates that greater the power output is, lower the PS should be. This finding reveals that macroeconomic growth has a significant negative effect on China's listed power companies' (CLCP) stock returns in the long run. This seemingly odd result is caused by the strong speculation that occurs in China's stock market (Dong and Wang[15]) and is policy-driven (Narayan and Zheng[33]), meaning that policies affect investors' sentiments more highly than economic growth. Moreover, although China's economic growth (power generation is an indicator of macroeconomic development) increased quickly in the period of this study, tightening policies during this period—such as raising the deposit reserve rate from 2.25% to 3.50% between December 23, 2008, and June 8, 2012, and strengthening the supervision of the power industry[5] ——jointly exerted negative impacts on changes in the power stock price.

The relationship between coal price (CP) and power stock price fluctuation is statistically significant with a negative value. This means the increase in coal price has a negative impact on power stock price fluctuation; coal price increase caused a decrease in generators' anticipated profit, and thus reduced the fund flowed into power stock market.

The positive correlation between fund supply on the stock market (FS) and power stock price volatility could be easily understood. Increase in the money supply will lead to additions of money liquidity and nominal wealth; thus, stock prices are more volatile.

The short-run dynamic changes of the relationship between power stock price and other variables (results of ECM) are shown in Table 8. The short-term impact of power market reform

[5] Over this period, more than 10 policies have been implemented to regulate power generators to develop energy savings and environmental protection

on power stock price volatility is similar to that in long run, which strengthens the result that China's power market reform reduced the stock price volatility of the listed power companies and the risk of investing in the power stock market. This implies that China's power market reform favors the expansion of power companies' ability to attract capital and promote power industrial development.

The only important difference between Table 8 and Table 7 is that the impact of the first policy (D1) on power stock price volatility becomes statistically significant in Table 8. Table 8 also indicates that the impacts of the control variables (PG, CP and FS) are consistent with the results in the long term. The most important difference between short term and long term is that the negative coefficient of dummy variable 1 is statistically significant in a short-run period. This indicates that the policy of *Measures of Price and Facility Operation of Desulphurization for Coal-fired Power Units* issued by NDRC reduced the fluctuation of power stock price in a short run. This policy aims to encourage coal-fired power firms to invest and operate the facilities of desulphurization. Since this policy is signaled by compulsory administrative characteristics, it affects power stock price only in a short run.

Table 8 ECM results

Variables	Coefficient	SD	T-statistics	P-value
ΔPG	-0.278***	0.108	-2.588	[0.01]
ΔCP	-0.174***	0.085	-2.236	[0.00]
ΔFS	0.383**	0.110	4.500	[0.03]
D1	-0.157**	0.073	-2.162	[0.03]
D2	-0.134***	0.042	-3.203	[0.00]
D3	-0.172***	0.044	-3.905	[0.00]
D4	-0.224***	0.049	-4.592	[0.00]
ECM(-1)	-0.154***	0.056	-2.741	[0.00]
R-Squared = 0.399	R-Bar-Squared = 0.325	F-Stat. F(7,66) = 6.169[0.00]		

***, **denote significance at the 1% and 5% levels, respectively.

As seen from Table 8, the coefficient of the error correction term is statistically significant at -0.154. This suggests that when power stock price volatility is above or below its equilibrium level, it adjusts by almost 15.4 % within the first year. The results support the notion that with the promulgation of a few power industrial policies, China's power stock price volatility tended to shrink because these regulations increased investors' confidence in the orderly development of China's power market.

5. Conclusion

As one of the important energy-intensive and emission-intensive sectors, China's power industry has increasingly attracted the attention of researchers and policymakers regarding

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how to promote more environmentally friendly development. One effective measure to improve energy efficiency is implementing power market reform (Zhao and Ma[34]; Du, et al.[35]; Ma and He[36]). However, possible negative impact of policies on stock price volatility is a concern for the issue of relative policies. The objective of this study is to explore the impact of China's power market reform on power stock price volatility and to determine which policies have the most important influence on volatility.

This paper used the ICSS algorithm to detect structural break points in power stock price volatility and analyzed volatility characteristics of sub-samples based on the GARCH (1, 1) model. We found that from August 30, 2006, to November 15, 2012, four structural breaks of China's power stock price volatility occurred, and three of them were related to the promulgation of power market reform policies. In addition, we found that the degree of power stock price fluctuations in each sub-sample decreased with time, indicating that China's power market reform reduces power stock price fluctuations.

To identify the above result and quantitatively study the impact of power market reform on power stock price volatility, we conducted an ARDL co-integration analysis using relative monthly data from August 30th, 2006, to November 15th, 2012. These results demonstrated that power industrial policies have a statistically significant negative impact on power stock price volatility, meaning that China's power industrial policy promoted the development of the power stock market by reducing market risks. We give explanations for policies with extreme volatility one by one in the fifth section along with the market conditions at that time. Moreover, the *Drawing the Roadmap for Deepened Reform for Power Development in the Twelfth Five-Year Plan Period* had the most important impact on power stock price volatility in the long-run period with the coefficient of -1.451, and in the short-run period with the coefficient of -0.224. These results indicate that compared to specific power regulation in Table3, overall strategic plan for industrial development are more important in terms of degree and scope of influence, thus has greater impact on the power stock market.

Our research controls for other factors in three ways. First, when we estimate the effect of one policy, the effects of the other policies are controlled. We incorporate all policy variables into the GARCH model simultaneously, allowing us to estimate each policy effect controlling for the effects of the other policies. Second, according to the properties of the GARCH model, the model describes the influence of all past and recent information shocks on volatility, capturing the total effect of the other factors at that time. When we incorporate the policy effects as explanatory variables of volatility, we separate out the policy impacts from the other effects. In other words, to some extent, we estimate policy effects while controlling for the total effect of the other factors indirectly. Third, we incorporate economic variables such as PMI, PPI, and GDP as explanatory variables into our model (i.e., directly control for the economic factors). Not only are none of these economic variables statistically significant, but they also do not affect the coefficients and significance of the policy variables. These results further show that the Chinese stock market is a typical policy-oriented market. Considering that economic factors are not the focus of this study, we do not demonstrate the relevant results for clarity. However, these tests can be regarded as alternative robustness tests.

The conclusion of this paper is based on samples from August 30, 2006, to November 15, 2012, in China. Future studies are required to determine whether the analysis can be expanded to a longer period or wider scope. Meanwhile, in addition to regulation reforms, there are other factors that would also contribute to the structure breaks of China's stock price volatility; however, these factors have not been considered in this study. In our future studies, we will explore how to examine these factors and exclude their interference in results.

6. Policy implications

Industrial policies in the power market aims to not only motivate the investment in renewable energy but also stabilize and even promote the stock price. Thus, when the government designs its policies related to investment behaviors, it should focus its attention on the linkage between different markets. Given our empirical analysis, we offer insights on further designs for and implications of industrial policy over power market.

Firstly, greater attention should be paid to policies promoting power market reforms in China. Few significant power industrial policies have been issued in China since 2003. The space for improving the energy efficiency of China's power industry is still significant. Current market-oriented regulation reforms have proven to be beneficial to the stability of China' s power stock market and favorable for power industry development.

Secondly, renewable energy policies should be promoted further, since it still has great potential to better attract investment in the power industry. However, our study indicates the recent policies related to renewable energy do not have a very significant impact on the power stock market. Our findings is consistent to other scholar's judgement. Bertrand Rioux.et al(2017) [47]shows neither restrictive tariff caps on coal-fired generation, nor the increase in the share of renewable energy have a significant effect on total generation with coal. A substantial reduction in coal use in China's energy system would require additional policy interventions.

Third, according to our empirical analysis, investors have paid considerable attention to the continuing implementation of the policy. Therefore, the government should make sure that the execution of the policy continues. The Chinese government should continually motivate power generators whose businesses focus on thermal power generation to invest in renewable energy with further detailed information in the execution and regulation.

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