A NEW PERSPECTIVE ON FINANCIAL ANOMALIES IN EMERGING MARKETS: THE CASE OF CHINA

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Abstract

Financial anomalies in emerging markets can be caused by very different reasons than that in mature markets. In a GARCH model, we examine financial anomalies in emerging markets from a new perspective, which focuses on heavy political interventions. In the context of China, we show that political consideration of the government can be a critical force that drives the monthly anomaly in the stock market. The Chinese case indicates that usual explanations for the month anomaly or the January effect may become invalid in an environment where political intervention is a dominant force in the stock market. Typical of a policy-driven market that prevails in emerging economies, results indicate no evidence for the January effect in China, neither its mirror version, the Chinese New Year effect. Rather, returns abnormality is found to occur in March when China is in the political high season. This March effect is likely a result of political manoeuvre by the government to make the appearance of a stable and thriving stock market, which serves the political purpose of preventing social resentment in a politically sensitive time. This shows political window dressing can be an important cause of financial anomalies, which has been largely neglected in the literature.

Key words: Deviation from CAPM; GARCH models; Holiday effect; Political intervention; Chinese economic policy

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I. Introduction

Financial anomalies have been well documented in the literature (Schwert, 2003). Many researchers have reported the existence of anomalies in different effects. Various factors causing the financial anomalies have also been unveiled. However, previous research focuses mainly on mature markets in North America and Europe. Anomaly analysis of emerging Asian markets is scant, and studies of anomalies in the Chinese stock market very few. This leaves a critical void in our knowledge of financial anomalies.

The Chinese stock market is one of the oldest in Asia, with its history dating back to 1860s when some Shanghai brokers started trading shares of foreign firms in China. By 1935, the Shanghai Stock Exchange had grown to become one of the biggest exchanges in Asia, only to be disrupted by the Second World War. During 1949 - 1952, the Chinese revolution eliminated private ownership and therefore stock trading.

The re-opening of stock exchanges in China was a result of sweeping economic reforms. To better channel funds into investment, the Chinese government sanctioned the opening of the Shanghai Stock Exchange (SHSE) in December 1990 and the Shenzhen Stock Exchange (SZSE) in July 1991.

Since then, the Chinese stock market has experienced rapid growth. China now boasts a stock market that is the largest in Asia after Japan. It is also the largest in the world of emerging capital markets. According to some estimation, the Chinese securities market has the potential to become among the major markets in the world.

But weak rule of law, inadequate institutions, lack of training for fund managers, and under-development of sophistication of ordinary investors, etc. are hitting China's nascent market. The government's interventions are only to make the situation even worse. As a result, there exhibit in the Chinese market considerable market distortions and deviations from what the efficient market hypothesis predicts, or financial anomalies. This makes China a weighty case for studying financial anomalies from the perspective of special institutional details typical in an emerging economy. Studies of financial anomalies from this perspective have been surprisingly neglected by the current literature.

Of all forms of financial anomalies, the monthly anomaly, especially the January effect is perhaps the best-known example.[1] Various hypotheses have been advanced to explain such an effect. For example, the tax-loss selling hypothesis claims that investors wait until the tax-year-end to sell their "loser" shares to realize capital losses that can offset capital gains. When investors in January buy back the stocks they sold, the selling pressure is relieved, resulting in large gains for loser stocks (Rozeff and Kinney, 1976; Poterba and Weisbenner, 2001). Other related studies in this field, e.g., Gibson, et al. (2000) identify a November effect, resulting from tax-loss selling by

[1] There is a vast body of literature on the January effect. For the sake of space, we cite only limited number of papers for each school of thought. See Chen and Singal (2004) and references therein.

mutual funds due to a change in the 1986 tax code in USA. Cataldo and Savege (2000) suggest a tax-gain selling hypothesis. Investors tend not to sell winner stocks in December to postpone realization of capital gains so that they can delay payment of taxes on capital gains for almost one year. This pushes up the prices of the winner stocks in December, leading to the December effect.

Recently, new research has emerged focusing on other non-mutually exclusive explanations for the monthly effect. This has led to the explanation that is related to errors in data collection or statistical methodology, such as in Keim (1989). According to this theory, the monthly effect is a result of the modelling misspecification which misses some risk factors in the particular month, say January. This means the monthly effect could be spurious and so investors cannot really trade at these prices.

Another explanation is based on new information provided by firms at the end of the fiscal year, this being known as the information hypothesis (Rozeff and Kinnery, 1976). Seasonal information flows may vary with different categories of investors, and so do the level and speed of information dissemination. Miller (1990) maintains that during Christmas people postpone what can be postponed including an investment decision, in order to buy gifts, leading to a reduction in the speed of their reaction to information, contributing to the January effect.

The window dressing theory is of particular interest. The theory attributes the monthly effect to the possibility that money managers may engage in some form of window dressing to promote positive perceptions of their performances in managing their clients' portfolios. This also implies that the January effect is caused by systematic shifts in the portfolio holdings of investors at the turn of the year (Haugen and Lakonishok, 1988).

The monthly effect has been generally viewed in previous research as a phenomenon of developed markets. However, new studies on emerging markets have recently appeared. For example, Fountas and Segredakis (2002) test for the January effect and the tax-loss selling hypothesis using monthly stock returns in eighteen emerging markets for 1987-1995. They found little evidence in favour of the January effect. Maghayereh (2003) investigates the seasonality of stock returns in the Jordanian financial market. Using the standard GARCH and EGARCH models of daily returns on the Amman Stock Exchange for the period 1994-2002, he finds no evidence of the January effect either.

Research on China is mostly concerned with the weak form efficiency of the Chinese market. Only a limited number of studies have so far examined specific forms of financial anomalies in the Chinese market, particularly calendar-related anomalies. Xu (2000) finds no day-of-the-week effect in Shanghai. But Chen, et al. (2001) investigated this effect and found a Tuesday anomaly during 1992–1997. Mookerjee and Yu (1999) find that, in China, the highest daily returns occur on Thursdays.

Mookerjee and Yu (1999) devote some part of their research to the turn-of-the month effect and the monthly effect. The turn of the month is defined as the first and last 9 days of the month. In passing, they find evidence that the turn-of-the-month effect exists in China. But their samples cover only 1990-1994 (for SHSE) and 1991-1994 (for SZSE). These were the opening years for both exchanges, during which large price fluctuations took place and construction of stock indices frequently changed.

In their research on the mechanism of asset pricing in China, Eun and Huang (2002) "incidentally" find no January effect in China, but August has the highest mean return of the year. Drew et al. (2003) construct portfolios sorted on firm size and book-to-market equity. They then investigate the seasonal behaviour of risk premium in a multifactor model with a dummy for the January effect and a February dummy for the effect of Chinese New Year, which usually falls in February. The results show no January or Chinese New Year effects on SHSE.

It can be seen then, the current state of research has provided only limited empirical evidence on the existence and nature of financial anomalies in China. Also, it is debatable that whether existing theories can afford adequate underpinning for understanding the monthly anomaly in China. The tax-related selling as the most important cause in the literature is irreverent in China's case because there is no capital-gains tax in China. Neither is it the practice for Chinese firms to publish information at the year-end, hence invalidates the information hypothesis. For the small firm effect, Seyhun (1993) shows that all firms, not just the small ones, should be included in any potential explanation for the January effect. For the hypothesis of modeling misspecification, because of the data availability, we are unable to use midpoint quotes to control market microstructure biases in data measurement as suggested by Chen and Singal (2004).

This leaves us to consider the window dressing hypothesis. This hypothesis is interesting because Chinese fund managers, as elsewhere, tend to maneuver the portfolios under their management to paint rosier their performance record, hence may cause the January or monthly effect in China. But why should they do this in a particular month, year in year out? More importantly, the institutional settings of China are such that fund managers are hardly a significant actor in moving the market. The more powerful force at work in the Chinese stock market is the interventionist Chinese government. It is the influence of this force that is the key to understand the financial anomalies in China. We argue that this makes a clear case for examining the role of government in causing financial anomalies in China, and more generally in emerging economies. We therefore argue for the necessity of studying financial anomalies in emerging markets with a new perspective that takes adequate consideration of these economies' institutional detail.

In what follows we will, in a GARCH model, carry out our empirical investigation along the line of the window dressing hypothesis with a perspective that focuses on the interventionist role of the government. The GARCH presentation has a number of advantages in modeling financial anomalies, which include its capability of capturing the stylized facts of financial data and incorporating heteroscedasticity into the modeling process. Its construction can also be flexible enough to allow for various dynamic structures of conditional variance.

Section II of this study briefly presents the distinctive character of the Chinese stock market, which is a market driven by government policy. Section III discusses the econometric formulation of the GARCH model that we employ to investigate the monthly anomalies in China. After Section IV which contains main empirical findings, Section V concludes the study.

II. The Policy-Driven Chinese Stock Market

The Chinese stock market is characterised by the fact that the government has the overwhelming influence. From the beginning, the Chinese government has created stock market institutions that allow the state to maintain control over listed companies and the market as a whole (Cooper, 2003). Heilmann (2002) calls it a policy-driven market since it is dominated by political calculations, policy missions and administrative interference.

The Chinese government has invented three different share categories. About a third of the shares are ordinary shares, which are tradable on the stock exchanges. Another third is made up of state shares that are not tradable. Legal person shares make up the final third. They represent the part of the firm owned by other state firms and cannot be traded on stock exchanges. [2]

This market segmentation leads to concentration of ownership by state and legal shareholders. As of the end of July 2004, about 64% of all Chinese shares are nontradable blocs held by state agencies and other state-owned firms. So, about two-

[2] Another form of market segmentation was related to A- and B-shares. A-shares were denominated in the Chinese currency (RMB) and owned by Chinese nationals. B-shares could only be purchased by foreign investors. They were quoted in RMB, but settled in US dollars (on SHSE), or Hong Kong dollars (on SZSE). From January 2001, Chinese citizens are allowed to trade in B-shares.

thirds of shares outstanding are controlled by the state or state-related entities, with individual holdings of shares being in the minority.

The market segmentation affects the risk profiles and future cash-flow opportunities of a company. Trading is thin while volatility is high and investors are discouraged from taking a buy-and-hold approach, fearing the government will one day dilute their holdings by releasing state shares (Eun and Huang, 2002).

In addition, capital controls in China has created barriers to the transmission of international price movements to China. There is even no transmission between SHSE and SZSE (Fabozzi et al., 2004). The divorce of the Chinese market from global forces means a pricing pattern that is different from that of international counterparts.

With capital controls, Chinese investors are deprived of the opportunity for international diversification. This further distorts investment decisions and hence pricing patterns. Furthermore, the long-term isolation implies that China misses out on the opportunity to learn and adopt international standards, resulting in a weak Chinese disclosure and legal environment, and a less transparent trading system.

Excessive price movement and speculative activities are common in China's stock market (Mei, et al., 2005). Using the Shanghai Composite Index and the NYSE Composite Index, Chow and Lawler (2003) report that the mean of weekly returns to Shanghai stocks is 17.5%, much higher than the mean for NYSE, which is only 9.48%. Also, volatility in Shanghai is much higher than in New York. In the initial public offering market, research findings have confirmed huge underpricing of Chinese IPOs.

The returns on Chinese new shares are the highest ever recorded in IPO markets around the world. From 1984 to 2000, the average initial return was 398% and the average first day return was 406%. In some years, the average initial returns would be more than 1000 % (Gu, 2003).

Using very high turnover as a symptom of a highly speculative stock market, Wang and Xu (2003) believe most Chinese investors have traded speculatively with very short holding periods. They report that, with round-trip trading costs approaching 1 % of the total transactions, the average annual turnover in China from 1996 to 2002 was 537% (Wang and Xu, 2003). In such a market environment, investors are more interested in short-term gains and tend to ignore long-term investment objectives.

The market segmentation, erratic pricing and excessive speculation undermine the government's agenda of financially supporting state enterprises through a growing capital market (Wong, 2005). In response, the government has intervened frequently. The intervention has taken various forms, including price regulations, special leader articles in government newspapers, secrete buying or selling transactions, and "meetings" with fund managers, etc.

One distinct feature of Chinese intervention is that, whereas the government had occasionally stepped in to calm the market when it was overheated, such as in 1996, 1997, and 1999, the intervention was predominantly aimed at popping up the slumping market. [3]

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[3] Finance and Economy Daily, 20 September 2005, (in Chinese).

The first known rescue operation was taken place in late 1992 when the Shanghai Index plunged to 386 point. The government managed to boost the market to 1172 point, an increase of more than 200%. In August 1994, a series of interventions resulted in the Shanghai Index rising by 120%, from 325 to 1052 point. In May 1995, interventions popped up the Shanghai Index from 547 to 926 point. The intervention in 1999 climaxed in the surge of stock prices in 19 May 1999, which marked the beginning of a bullish market that was to last for two years. In 2001 and 2002, the Chinese market continued to receive bolstering from the government (Lin, 2005).
In addition to support the market in large market declines, the government has also engaged in popping up the market during politically sensitive periods. There are increasing reports that every year around March, the government summons fund managers and banking officials to Beijing for talks on achieving "social stability". March is a special month in China because in this month it will be held the yearly National Plenary Conferences of People's Representatives and of People's Political Consultation, known as the Two Great Conferences. During this period, a series of political drama would unfold, including policy debates, cabinet reshuffles, and meeting-the-press by top Chinese leaders. These events are rare in an otherwise tightly concealed country. The eventful March therefore marks the high season of Chinese politics and attracts a lot of international media attention.

In this setting, social unrests would cause more media sensation and more deeply felt around the world, hence have much stronger effects than otherwise in other months. Due to sweeping economic transformation and complex regrouping of social interests, China in recent years has experienced a huge number of social unrests. Of the triggering mechanisms for the eruption of interest conflicts the stock market is particularly prone to be a hotbed for nourishing public resentment against political establishment in China. By its very nature, the stock market tends to land extreme wealth to a handful of people, only at the cost of a much large number of investors. The structure of China's stock market is such that most investors are individuals with low income and they are in huge numbers. With limited financial resources and little experience in risk management, they are very vulnerable to erratic price fluctuations. A small ripple of price movements therefore will drown a huge number of small investors. To make the situation worse, many of them gamble in the stock market with their life savings for pension. This makes the Chinese stock market a nightmare for the government; disruptive price changes threaten large scale social instability. In March, this would have magnifying effects. Hence, in the high season of Chinese politics in March, the government has every reason to window dress the stock market performance, to pre-empt the outbreak of general turmoil.[4]

Against this background, we conjecture that political window dressing is plausibly a fundamental cause of seasonal anomalies in China. While monthly anomaly is unlikely to appear in January due to reasons mentioned above, given China's internal political process and institutional settings, it would be interesting to examine whether financial anomalies appear in the high political season of March. Evidence of this effect may enable us to add to the literature political window dressing as a plausible explanation for the monthly effect.

[4] "Understanding the Prime Minister's determination of "rescuing the market" in its true perspective", China Economic Times, 17 March 2005, in Chinese.

III. Econometric Formulation

Given the policy-driven nature of the Chinese stock market, we deploy ARCH/GARCH models to investigate the January effect in China. Because of a number of attractions, the ARCH family models have been frequently used to model stock price anomalies e.g., Choudhry (2001). In this regard, the advantages of ARCH family models include its facility of capturing stylized facts of financial series such as fat tails, volatility clustering, etc. By modelling the conditional variance as a measure of risk, not only are the deficiencies of OLS corrected, but a prediction can be computed for the variance of each error term (Engle, 1982). Because of its advantages, ARCH/GARCH models can have applications to numerous and diverse areas.

Following Engle (1982), the ARCH model can be expressed as:

(1) $$y_t = \beta_1 + \beta_2 x_{2t} + u_t \qquad u_t \sim \mathrm{N}(0, \sigma_t^2)$$

(2) $$h_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

Equation (1) is the equation for the conditional mean, which may take any form. Equation (2) is the conditional variance equation. In this formulation, the autocorrelation in volatility is modelled by allowing the conditional variance of the error term, h_t^2 to depend on the immediately previous value of the squared error as in Equation (2). Although h_t^2 depends on only one lagged squared error in Equation (2), it can be extended to the general case of q lags.

However, the value of q, or the number of lags of $\hat{u}_t^2$ is difficult to decide. The lagged value of q may be very big to capture the dependence in the conditional variance, leading to a non-parsimonious model. Moreover, in a large model, the non-negativity constraints may be violated. This is because the conditional variance h_t^2 must be strictly positive as it is squared, which implies that all coefficients on all squares of lagged errors are non-negative to ensure a strictly positive conditional variance.

To overcome some of the problems, Bollerslev (1986) proposes the generalised ARCH model, or the GARCH model, which extends Equation (2) to:

(3) $$h_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \phi_1 h_{t-1}^2$$

This adds an autoregressive component $\phi_1 h_{t-1}^2$ to the moving average component. In Equation (3), h_t^2 is known as the conditional variance, α_0 is a long-term average value, $\alpha_1 u_{t-1}^2$ gives the information about volatility during the previous period, and $\phi_1 h_{t-1}^2$ is the fitted variance from the model during the previous period. So, in the GARCH model, the conditional variance h_t^2 is a weighted function of these three items. To ensure non-negative constraints, some restrictions are needed:

$$\alpha_0 > 0$$
$$\alpha_1 \geq 0 \qquad for\ i = 1, \quad \ldots, \quad p$$
$$\phi_1 \geq 0 \qquad for\ i = 1, \quad \ldots, \quad q$$

From Equation (3), the conditional variance is changing, but the unconditional variance is constant and given by:

$$\text{var}\ (u_t) = \frac{\alpha_0}{1-(\alpha_1+\phi_1)} \qquad for\ \alpha_1 + \phi_1 < 1. \quad For\ \alpha_1 + \phi_1 \geq 1, \quad not\ defined.$$

Like ARCH (q), there can be any number of lags for GARCH.

Like the ARCH representation, the GARCH model can capture the stylised facts of financial data and incorporate heteroscedasticity into the estimation procedure. Its construction of the lag structure can be very flexible to allow for various dynamic structures of conditional variance. So the GARCH model is capable of modelling quite complicated patterns of heteroskedasticity with relatively low orders of q. As such, the GARCH is more parsimonious and avoids overfitting, hence is less likely to breach non-negativity constraints, which is its main advantage over the ARCH model. The GARCH model can also be cast in a multivariate setting to simultaneously estimate several parameters and hypotheses (Chou, 1988).

Many extensions have been proposed for the GARCH model, such as the GARCH-in-Mean model, the GLR model, and the EGARCH model. We test for the January effect and monthly effect in the Chinese stock market using a GARCH in mean or GARCH-M model with Student-t distributed errors plus an MA(1) process, or an MA(1)-GARCH (1,1)-t-M model, with the mean equation being specified as:

(4) $$R_t = \alpha_0 + \delta_i x_{it} + \phi h_{it}^{\lambda} + \varepsilon_t + \theta \varepsilon_{t-1}$$

where R_t is the stock returns assumed to be linearly dependent on a vector of explanatory variables (x_{it}), the conditional variance (h_{it}^{λ}) and an error term (ε_t), plus a moving average term $\theta \varepsilon_{t-1}$. In the regression, α, δ, and θ are parameters. The x_{it} term is a vector of monthly dummy variables, such that $x_{it} = 1$, for the ith month and zero otherwise. This applies to January through to November, and so the intercept

α_0 represents the effect of the December dummy. The coefficients δ_{Jan} to δ_{Nov} plus α_0 are then the mean returns for the year. For the presence of the January effect, the coefficient of the January dummy should be significantly positive in the regression.

The adoption of the GARCH in the mean model is due to Susmel and Engle (1994). They propose that, given the fact that in finance models an increase in variance (risk) is related to higher expected returns in share prices, it is appropriate to extend the standard GARCH to the GARCH in the mean or GARCH-M model.
The inclusion of the MA term is in order to capture the effect of negative serial correlation induced by non-synchronous trading as suggested by Susmel and Engle (1994). This has been followed in many recent studies (Choudhry, 2001; Maghayereh, 2003). Given the property of the data series in this study, the error terms are assumed to follow a conditional Student-t density. In other words, the model assumes the error distribution to be conditionally heteroscedastic and non-normal. These are the two major sources of unconditional leptokurtosis and so the model specification will allow us to cope with such leptokurtosis.

We employ monthly data during the period from January 1992 through to December 2003. All the data sets are obtained from the Chinese Stock Markets and Accounting Research (CSMAR). In total, we collected six market indices. We have the SHSE-A index for A-shares listed on the Shanghai Stock Exchange, the SHSE-B index for Shanghai listed B-shares, and then the SHSE-C index that combines all shares listed on the Shanghai Stock Exchange. In addition, we have the SZSE-A index for A-shares listed on SZSE, the SZSE-B for B-shares listed on SZSE and SZSE-C for a composite market index on SZSE. Because of data availability, the SZSE-A index and the SZSE-B index range from October 1992 to December 2003, while the SZSE-C index is from January 1992 to December 2003.

These stock price indices are value-weighted; all listed firms are given weights based on their shares of market value. The indices have been adjusted for stock splits, new issues, and rights issues. None of these indices includes dividend yield since little difference will be made by the use of dividend adjusted or unadjusted stock returns.

In our empirical estimation, stock returns (R_t) are represented by the first difference of the log of stock price indices. We first inspect the returns series to examine how they evolve during the sample period. The plots below show that for most of the time there are large swings in returns and only in recent years have they gradually moved towards normal.

[Figure I. approximately here]

Because of the property of financial data, it is reasonable to base inference on returns. Furthermore, asset prices generally have a unit root, whereas changes in the logarithm of price are usually stationary. To check the time series property, and hence the stochastic structure of the data series, the augmented Dickey-Fuller test is applied (Table 1).

[Table 1 approximately here]

The null hypothesis of a unit root can be rejected for all six returns series, implying all series are stationary. For other basic descriptive statistics of the six stock return series, see Table 2.

[Table 2 here]

It can be seen from Table 2, the distributions of all six series are skewed. Furthermore, all series have excess kurtosis so the distributions are leptokurtic, which gives further evidence for non-normal distribution of the returns. The Jarque-Bera tests formally confirm that, for all six series, the null hypothesis of a normal distribution can be rejected, which is consistent with findings in other research e.g. Bollerslev (1987), these characteristics suggest that it is fitting to use an ARCH class of models.

IV. Empirical Results

Test Results for A-Shares Markets

Since the GARCH model is no longer linear, we use the maximum likelihood technique rather than OLS for estimation. The model estimation starts by specifying the mean equation and the variance equation. Following Fabozzi, et al. (2004), we chose (p. q) to be (1,1) for our estimation. Table 3 presents the results for A-shares in both the Shanghai and Shenzhen Stock Exchanges from the MA(1)-GARCH-t in the mean model, with monthly dummies in the mean equation.

[Table 3 here]

The ARCH process or volatility clustering seems not to be present in A-shares, since for neither exchange is α_1 significant. The coefficient on the MA term is negative and significant in Shanghai A-shares returns, which indicates that they exhibit serial correlation. We notice that this is not the case for Shenzhen.

For our main concerns, the estimated value of the intercept and the coefficients of the monthly dummies in the mean equation show no significant January effect. The January dummies are not significant and so the January effect does not exist in the Chinese A-shares market.

The absence of the January effect in the Chinese A-shares market can primarily be explained by the fact that, as China has no tax on capital gains, there is no pressure on investors to sell their loser stocks at the tax-year-end to realize capital losses that are used to offset capital gains, as suggested by the tax-loss selling hypothesis.
Contrary to some reports that there is a Chinese New Year effect in China's stock market, the results in Table 3 also show no significant difference in returns in February than in any other month. Unlike the Christmas effect in North America or Europe where people may withdraw funds from shares to finance Christmas shopping, it is not Chinese tradition for investors to sell stocks for the Spring Festival shopping.

Interestingly, we find a significant and positive effect in March. As discussed before, the month of March marks the high season of Chinese politics during which the Two Great Conferences will be held. During this politically sensitive time, the Chinese authorities tend to create a celebratory atmosphere for the month of March, including popping up the performance or at least no large slumping of stock market. We call this as political window dressing of the stock market. Our empirical evidence reveals this effect in March.

Test Results for B-Shares Markets

Next, we examine monthly anomalies in China's B-shares market. The chief difference between the A- and B-shares market is that, for most of its life, the B-shares market was accessible only to foreign investors. Table 4 reports how the foreign investors have behaved in the Chinese B-shares market.

[Table 4 here]

Table 4 shows monthly changes in B-shares returns in both Shanghai and Shenzhen Stock Exchanges. There is an MA (1) effect in both exchanges, although in the Shenzhen market the effect is relatively weak (significant at the 10% level). More importantly, in both exchanges, there is no monthly effect at all. Neither the January effect nor the February Chinese New Year effect is present. Neither is the March political window-dressing effect is significant. This suggests that the Chinese authorities' intervention in the stock market follows a strategy that concentrates on the domestic segment while carefully avoiding interfering with foreign investors.

Test Results for All Shares Composite Indices

Finally, we investigate the monthly anomalies in the Chinese stock market by way of composite market indices, i.e. both the Shanghai composite index (SHSE-C) and the Shenzhen composite index (SZSE-C). These indices cover A-shares as well as B-shares. Table 5 reports the test results for the all shares composite index on SHSE.

[Table 5 here]

Test results of the Shenzhen all shares composite index are collected in Table 6.

[Table 6 here]

The two tables both show the March effect exists in the Chinese stock market. In the case of Shenzhen, this effect would even last into April. A possible explanation for this longer effect may be that, in addition to central authorities' intervention, Shenzhen local government may have intervened in the stock market as well because of its proximity to Hong Kong. Apart from this effect, once again there is no evidence of a January effect or February Chinese New Year effect in the overall indices.

Model Specification Tests

At the bottom of each table, we report the outcome of specification tests for each of the six models. The testing procedures follow Engle and Patton (2001), which focus on checking whether the specified GARCH models capture the heteroskedasticity and persistence in the variance adequately. The standardized residuals are first calculated using the residuals ($\hat{\varepsilon}$) from the respective mean equation in GARCH models and the fitted conditional variance ($\hat{h}_t$), such that $\hat{z}_t = \hat{\varepsilon}_t / \sqrt{\hat{h}_t}$. We then check the normality of the series of standardized residuals. Next, the standardized residuals are squared and we then check whether they are serially uncorrelated. Finally, the standardized residuals are subjected to the Portmanteau test for the existence of serial correlation.

The ARCH of squared standardized residuals is tested with the F-statistic and the normality test of residuals is tested with a χ^2 test. The null hypothesis of the ARCH test is that the coefficients of the autoregressive model for the residuals are jointly equal to zero. The results of the ARCH test reported in the tables show the GARCH models have eliminated the autoregressive conditional heteroscedasticity.

The Portmanteau statistics are the Box-Ljung Q statistics with a χ^2 distribution. The null hypothesis is that no serial correlation exists. Up to lag 36, the Portmanteau test suggests this hypothesis can be accepted for all the models.

Some of the normality tests failed, which is not surprising given the large extreme values in China's stock returns, and is consistent with similar volatility research on the Chinese stock market (Fabozzi, et al., 2004). Overall, the specification test results suggest the GARCH models employed are satisfactory in capturing the volatility dynamics of monthly effect on the Chinese stock market.

V. Conclusion

Financial anomalies are well documented in the literature. Various theories have been advanced to provide explanations for their existence. This research argues that, in the context of emerging markets, a clear case can be made to examine the role of the government in causing financial anomalies. This implies there is a political dimension of financial anomalies in the emerging world and we show that, with the evidence from China, government intervention could cause stock prices to deviate from what the efficient market hypothesis predicts.

With monthly data from January 1992 through to December 2003, we test for six market indices of the Chinese stock market including value-weighted indices of the A-Shares, B-Shares, and All Shares on the Shanghai and Shenzhen stock exchanges. Test results show it is fitting to use GARCH models to investigate monthly anomalies in China.

Based on log-likelihood and AIC and SIC test outcome, A GARCH in mean with Student-t distributed errors plus an MA (1) model is used in empirical investigation. Test results show that there is no January effect or the February Chinese New Year effect in the Chinese stock market. Instead, we find a significant and positive March effect.

Absence of the January effect can be mainly attributed to institutional details in China. The country does not have tax on capital gains, which is perhaps the most important cause of the monthly anomaly identified in the current anomaly literature on mature markets. The finding of the March effect in China reveals the political nature of financial anomalies in that country. This March political window-dressing effect is plausibly caused by political manoeuvre by the Chinese government. In this politically sensitive month of March, the government tends to pop up stock prices to window dress the stock market performance with a view to making the public feel good, to preventing the possible outbreak of general resentment and hence to maintaining social stability. This finding suggests that political window dressing is likely to be a fundamental cause of seasonal anomalies in China, which represents a new perspective that is also inspirational for understanding financial anomalies in other emerging economies.

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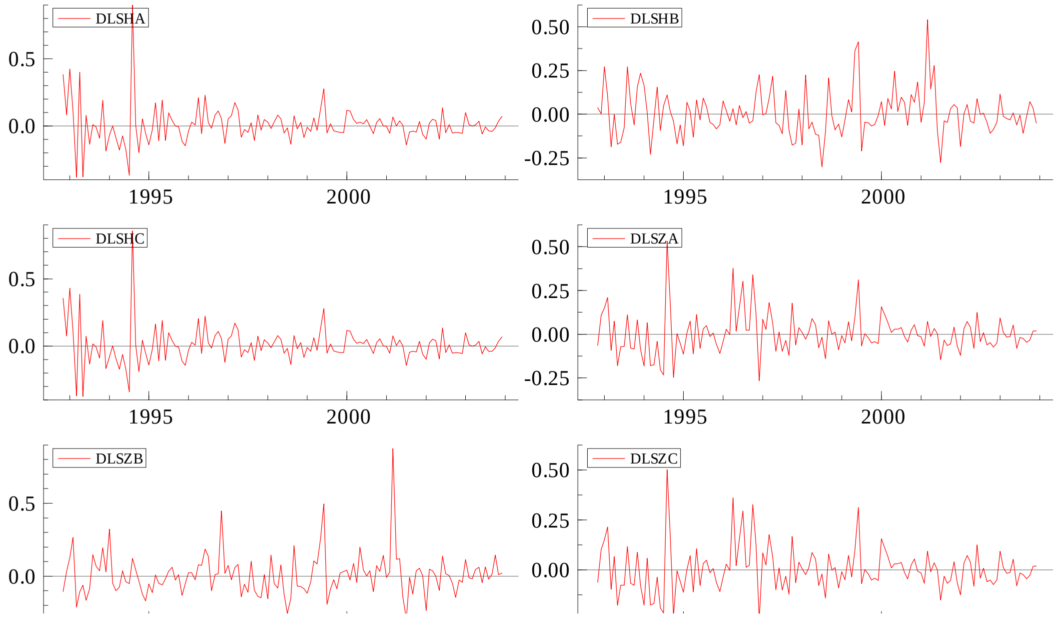

Figure 1 Stock Returns on the Chinese Market

Table 1 Time Series Properties of the Data 1993 (2) – 2003 (12)

Augmented Dickey-Fuller test for DLSHA:

	Coefficient	Std.Error	t-value
DLSHA_1	-1.5435	0.19944	-7.7394
Constant	0.0028142	0.011246	0.25023
DDLSHA_1	0.23272	0.16691	1.3943
DDLSHA_2	0.13923	0.12972	1.0732
DDLSHA_3	0.13375	0.080888	1.6535

sigma=0.127731 DW=1.928 DW-DLSHA=2.49 ADF-DLSHA=-7.739**
Critical values used in ADF test: 5%=-2.884, 1%=-3.481
RSS = 2.039416107 for 5 variables and 130 observations

Augmented Dickey-Fuller test for DLSHB

	Coefficient	Std.Error	t-value
DLSHB_1	-0.93930	0.15503	-6.0587
Constant	0.0033515	0.011311	0.29631
DDLSHB_1	0.14062	0.13451	1.0454
DDLSHB_2	0.073259	0.11209	0.65360
DDLSHB_3	0.068212	0.087834	0.77660

sigma=0.128562 DW=1.975 DW-DLSHB=1.582 ADF-DLSHB=-.059**
Critical values used in ADF test: 5%=-2.884, 1%=-3.481
RSS = 2.066028805 for 5 variables and 130 observations

Augmented Dickey-Fuller test for DLSHC

	Coefficient	Std.Error	t-value
DLSHC_1	-1.5222	0.19710	-7.7227
Constant	0.0026570	0.010911	0.24351
DDLSHC_1	0.22346	0.16514	1.3532
DDLSHC_2	0.13772	0.12890	1.0685
DDLSHC_3	0.13724	0.080866	1.6972

sigma=0.12393 DW=1.93 DW-DLSHC=2.472 ADF-DLSHC=-7.723**
Critical values used in ADF test: 5%=-2.884, 1%=-3.481
RSS = 1.919778235 for 5 variables and 130 observations

Augmented Dickey-Fuller test for DLSZA

	Coefficient	Std.Error	t-value
DLSZA_1	-0.94925	0.16932	-5.6062
Constant	0.00028297	0.0099663	0.028392
DDLSZA_1	-0.026452	0.15073	-0.17549
DDLSZA_2	-0.12704	0.12010	-1.0578
DDLSZA_3	0.045062	0.087166	0.51696

sigma=0.11344 DW=1.974 DW-DLSZA=1.968 ADF-DLSZA=-5.606**
Critical values used in ADF test: 5%=-2.884, 1%=-3.481
RSS = 1.608545702 for 5 variables and 130 observations

Augmented Dickey-Fuller test for DLSZB

	Coefficient	Std.Error	t-value
DLSZB_1	-0.98025	0.15821	-6.1960
Constant	0.0062630	0.012506	0.50080
DDLSZB_1	0.099779	0.13739	0.72626
DDLSZB_2	0.13228	0.11617	1.1387
DDLSZB_3	0.091544	0.087941	1.0410

sigma=0.14178 DW=1.919 DW-DLSZB=1.676 ADF-DLSZB=-6.196**
Critical values used in ADF test: 5%=-2.884, 1%=-3.481
RSS = 2.512791179 for 5 variables and 130 observations

Augmented Dickey-Fuller test for DLSZC

	Coefficient	Std.Error	t-value
DLSZC_1	-0.94839	0.16838	-5.6325
Constant	0.00040132	0.0097066	0.041345
DDLSZC_1	-0.027040	0.14978	-0.18053
DDLSZC_2	-0.11397	0.11996	-0.95007
DDLSZC_3	0.045282	0.087066	0.52009

sigma=0.11047 DW=1.971 DW-DLSZC=1.956 ADF-DLSZC=-5.632**
Critical values used in ADF test: 5%=-2.884, 1%=-3.481
RSS = 1.525394369 for 5 variables and 130 observations

Table 2 Descriptive Statistics of Chinese Share's Returns Data

1992 (11) - 2003 (12)

Normality test for DLSHA	Normality test for DLSHB
Mean 0.0083564	Mean 0.0063869
Std.Devn. 0.14055	Std.Devn. 0.12949
Skewness 1.9578	Skewness 0.90647
Excess Kurtosis 12.116	Excess Kurtosis 2.1068
Minimum -0.38093	Minimum -0.30219
Maximum 0.89880	Maximum 0.53990
Asymptotic test:Chi^2(2) =905.27 [0.00]**	Asymptotic test:Chi^2(2) =43.133 [0.00]**
Normality test: Chi^2(2) =56.306 [0.00]**	Normality test: Chi^2(2) =15.771 [0.00]**
Normality test for DLSHC	Normality test for DLSZA
Mean 0.0080764	Mean 0.0035754
Std.Devn. 0.13618	Std.Devn. 0.11456
Skewness 1.8836	Skewness 1.1605
Excess Kurtosis 11.318	Excess Kurtosis 3.7893
Minimum -0.37328	Minimum -0.26475
Maximum 0.85520	Maximum 0.53272
Asymptotic test:Chi^2(2) = 794.47 [0.00]**	Asymptotic test:Chi^2(2) =110.25 [0.00]**
Normality test: Chi^2(2) = 54.149 [0.00]**	Normality test: Chi^2(2) =23.855 [0.00]**
Normality test for DLSZB	Normality test for DLSZC
Mean 0.0087205	Mean 0.0036663
Std.Devn. 0.14143	Std.Devn. 0.11133
Skewness 2.1649	Skewness 1.1233
Excess Kurtosis 10.363	Excess Kurtosis 3.3177
Minimum -0.29451	Minimum -0.24803
Maximum 0.87599	Maximum 0.50162
Asymptotic test:Chi^2(2) =704.26 [0.00]**	Asymptotic test:Chi^2(2) =89.634 [0.00]**
Normality test: Chi^2(2) =53.558 [0.00]**	Normality test: Chi^2(2) =22.021 [0.00]**

Table 3 MA(1)-GARCH-t in the Mean test for Chinese A Shares
1993 (1) to 2003 (12)

Modelling DLSHA by GARCHM_t(1,1,"sqrt")

	Coefficient	robust-SE	t-value
Constant	-0.0336640	0.04328	-0.778
MA-SHA_1	-0.225646	0.07455	-3.03
Jan	-0.0116233	0.03157	-0.368
Feb	-0.00179733	0.03578	-0.0502
March	0.0721976	0.02133	3.38
April	0.0442830	0.04253	1.04
May	0.0462934	0.05344	0.866
June	-0.00194040	0.04157	-0.0467
July	-0.0224414	0.07843	-0.286
Aug	-0.0197678	0.07167	-0.276
Sept	-0.0182216	0.03362	-0.542
Oct	-0.0145241	0.04088	-0.355
Nov	0.0139063	0.05309	0.262
alpha_0	0.00140617	0.002820	0.499
alpha_1	1.63108	1.017	1.60
beta_1	0.0300168	0.1333	0.225
student-t df	11.4906	66.86	0.172
sqrt(h_t)	0.263006	0.2090	1.26

log-likelihood 130.743834 HMSE 2.33472
AIC.T -225.487668 AIC -1.70823991

Normality test: Chi^2(2) = 1.8817 [0.3903]
ARCH 1-2 test: F(2,110) = 0.66498 [0.5163]
Portmanteau(36): Chi^2(36)= 38.541 [0.3554]

Modelling DLSZA by GARCHM_t(1,1,"sqrt")

	Coefficient	robust-SE	t-value
Constant	-0.0625953	0.1537	-0.407
MA-SZA_1	-0.0447668	0.4686	-0.0955
Jan	0.0436392	0.08740	0.499
Feb	0.0522328	0.03917	1.33
March	0.0887222	0.03187	2.78
April	0.0534580	0.08751	0.611
May	0.0759365	0.04581	1.66
June	0.0416214	0.05192	0.802
July	0.0101327	0.06659	0.152
Aug	0.0335728	0.05329	0.630
Sept	0.00611995	0.07271	0.0842
Oct	0.0244666	0.1046	0.234
Nov	0.0541350	0.04584	1.18
alpha_0	0.000755012	0.01038	0.0728
alpha_1	0.206865	1.443	0.143
beta_1	0.760495	1.863	0.408
student-t df	3.28351	1.628	2.02
sqrt(h_t)	0.177944	1.231	0.145

log-likelihood 125.823014 HMSE 7.91411
AIC.T -215.646028 AIC -1.63368203

Normality test: Chi^2(2) = 31.727 [0.0000]**
ARCH 1-2 test: F(2,110) = 0.13148 [0.8769]
Portmanteau(36): Chi^2(36)= 47.140 [0.1012]

Table 4 MA(1)-GARCH-t in the Mean test for Chinese B-Shares
1993 (1) to 2003 (12)

Modelling DLSHB by GARCHM_t(1,1,"sqrt")

	Coefficient	robust-SE	t-value
Constant	0.166918	0.09124	1.83
MA-SHB_1	0.203880	0.08389	2.43
Jan	-0.0562208	0.08244	-0.682
Feb	6.76207e-005	0.04432	0.00153
March	-0.0196745	0.05399	-0.364
April	-0.0199922	0.04493	-0.445
May	0.00475225	0.07830	0.0607
June	-0.0592405	0.04771	-1.24
July	-0.0582379	0.05886	-0.990
Aug	0.0156850	0.04590	0.342
Sept	-0.0545935	0.04305	-1.27
Oct	-0.0506458	0.04524	-1.12
Nov	-0.0414197	0.05022	-0.825
alpha_0	0.00356780	0.002405	1.48
alpha_1	0.0542777	0.05139	1.06
beta_1	0.700660	0.1612	4.35
student-t df	5.19183	3.735	1.39
sqrt(h_t)	-1.18917	0.6831	-1.74

log-likelihood 95.4569583 HMSE 4.635
AIC.T -154.913917 AIC -1.17359028

Normality test: Chi^2(2) = 18.671 [0.0001]**
ARCH 1-2 test: F(2,110) = 0.26220 [0.7698]
Portmanteau(36): Chi^2(36)= 30.671 [0.7198]

Modelling DLSZB by GARCHM_t(1,1,"sqrt")

	Coefficient	robust-SE	t-value
Constant	0.187998	0.1253	1.50
MA-SZB_1	0.139442	0.08168	1.71
Jan	0.00486846	0.05387	0.0904
Feb	0.000264777	0.03254	0.00814
March	0.0166015	0.03444	0.482
April	0.0101094	0.03440	0.294
May	0.0454927	0.04935	0.922
June	-0.0165597	0.03860	-0.429
July	-0.0254967	0.04100	-0.622
Aug	0.0346490	0.03968	0.873
Sept	-0.0147294	0.03436	-0.429
Oct	0.000401728	0.03769	0.0107
Nov	-0.00217371	0.04291	-0.0507
alpha_0	0.00510484	0.004454	1.15
alpha_1	0.0646574	0.09458	0.684
beta_1	0.669654	0.2205	3.04
student-t df	3.04623	0.9652	3.16
sqrt(h_t)	-1.43417	0.8278	-1.73

log-likelihood 97.1245835 HMSE 17.042
AIC.T -158.249167 AIC -1.19885733

Normality test: Chi^2(2) = 78.697 [0.0000]**
ARCH 1-2 test: F(2,110) = 0.048970 [0.9522]
Portmanteau(36): Chi^2(36)= 32.681 [0.6272]

Table 5 MA(1)-GARCH-t in Mean test for All Shares on SHSE
1993 (1) to 2003 (12)

Modelling DLSHC by GARCHM_t(1,1,"sqrt")

	Coefficient	Std.Error	robust-SE	t-value	t-prob
Constant	-0.0352532	0.02189	0.04286	-0.823	0.412
MA-SHC_1	-0.229133	0.07507	0.07640	-3.00	0.003
Jan	-0.0113571	0.02303	0.02909	-0.390	0.697
Feb	0.000291130	0.02066	0.02873	0.0101	0.992
March	0.0712453	0.01890	0.02302	3.10	0.002
April	0.0460206	0.02312	0.03968	1.16	0.249
May	0.0501289	0.02467	0.04257	1.18	0.241
June	-0.00252459	0.02413	0.03932	-0.0642	0.949
July	-0.0184323	0.03988	0.08740	-0.211	0.833
Aug	-0.0165166	0.02785	0.05156	-0.320	0.749
Sept	-0.0164627	0.01989	0.02674	-0.616	0.539
Oct	-0.0125958	0.02228	0.03961	-0.318	0.751
Nov	0.0159056	0.02610	0.05041	0.316	0.753
alpha_0	0.00154443	0.001078	0.001851	0.834	0.406
alpha_1	1.59885	0.5883	0.9145	1.75	0.083
beta_1	0.0261243	0.05175	0.06602	0.396	0.693
student-t df	8.64385	12.55	25.63	0.337	0.737
sqrt(h_t)	0.270320	0.1311	0.2234	1.21	0.229

log-likelihood	131.974291	HMSE	2.41533
AIC.T	-227.948583	AIC	-1.7268832

Normality test:	Chi^2(2) =	2.6557	[0.2650]
ARCH 1-2 test:	F(2,110) =	0.86073	[0.4257]
Portmanteau(36):	Chi^2(36)=	40.058	[0.2948]

Table 6 MA(1)-GARCH-t in the Mean test for All Shares on SHZA
1993 (1) to 2003 (12)

```
Modelling DLSZC by restricted GARCHM_t(1,1,"sqrt")
              Coefficient  Std.Error  robust-SE  t-value  t-prob
Constant       -0.0494476    0.02820    0.03507    -1.41   0.161
MA-SZC_1       0.00233368    0.08054     0.1004   0.0232   0.981
Jan             0.0527458    0.03665    0.06015    0.877   0.382
Feb             0.0567124    0.02850    0.02754     2.06   0.042
March           0.0876233    0.03241    0.04413     1.99   0.050
April           0.0491606    0.02819    0.02761     1.78   0.078
May             0.0689626    0.03089    0.04076     1.69   0.093
June            0.0360074    0.03690    0.06078    0.592   0.555
July           0.00464249    0.02907    0.03278    0.142   0.888
Aug             0.0316957    0.02688    0.02320     1.37   0.175
Sept           0.00166871    0.02636    0.02265   0.0737   0.941
Oct             0.0166920    0.02688    0.02410    0.693   0.490
Nov             0.0528097    0.02806    0.03030     1.74   0.084
alpha_0      5.72173e-006  0.0001965  0.0003292   0.0174   0.986
alpha_1         0.0482241    0.06611     0.1337    0.361   0.719
beta_1           0.937539    0.06938     0.1374     6.82   0.000
student-t df      3.77077      1.306      1.978     1.91   0.059
sqrt(h_t)       0.0860573     0.2554     0.3655    0.235   0.814

log-likelihood     127.300815  HMSE                 6.41993
AIC.T              -218.60163  AIC              -1.65607296

Normality test:   Chi^2(2) =   18.730 [0.0001]**
ARCH 1-2 test:    F(2,110) = 0.027947 [0.9724]
Portmanteau(36):  Chi^2(36)=   40.374 [0.2830]
```