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The Impact of Short Selling and Margin Trading Regulation on Information Efficiency in China

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Abstract

We investigate the impact of short selling and margin trading on measures of information efficiency, the distributional characteristics of stock returns, and price clustering in the Chinese equity market. Short selling and margin trading were permitted for selected stocks from 31 March 2010 onwards and were subsequently extended to further securities on 5 December 2011. First, we find that the regulatory change does not have a consistent impact on the various information efficiency measures. Second, lifting short sale constraints significantly reduces skewness. Third, the avoidance of numbers ending in 4, which is considered an unlucky number in China, has marginally been reduced following the regulatory change. Overall, the mixed evidence suggests a slight improvement in price efficiency.

Keywords**:** Short Selling, Margin Trading, Information Efficiency, Stock Return Distributions, Number Preferences

JEL classification: G10, G12, G14, G18

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中国融资融券规则对其信息效率的影响

Saqib Sharif

摘要

我们调查了融资融券交易对中国股票市场信息效率、股票收益分布特征和价格聚类的影响。自 2010 年 3 月 31 日起，中国允许对特定股票进行融资融券交易，随后在 2011 年 12 月 5 日扩大到更多证券。首先，我们发现监管变化对各种信息效率度量并没有一致的影响。其次，解除卖空限制，使偏度明显降低。第三，4 被认为是不吉利的，对以 4 结尾数字的避免随着法规的改变而略微减少。总体而言，混合的证据显示价格效率略有改善。

关键词：卖空、融资融券交易、信息效率、股票回报分布、数字偏好

I. Introduction

It is generally accepted that allowing short selling makes prices more efficient.[1] As Li (2008, p. 88) notes in regard to the Chinese equity market, "[i]n stock markets where informational asymmetry and investors' irrationalities seem to be inevitable, short sales are … indispensable for improving market inefficiency".

The China Securities Regulatory Commission (CSRC) allowed a pilot short selling and margin trading programme in 90 A-shares effective from 31 March 2010 (Bryan *et al.*, 2010). Subsequently, effective from 5 December 2011, short selling and margin trading were permitted for a further 197 securities (hereinafter referred to as the affected securities) and more securities brokers were allowed to participate in the securities lending business.[2,3] These initiatives occurred at a time when financial regulators around the world were devising new rules to curb short selling to deal with the aftershocks of the global financial crisis (GFC) and the eurozone debt crisis (O'Sullivan and Kinsella, 2012).

We examine the impact of the introduction and expansion of short selling and margin trading in China on price efficiency. The role of short sellers in the price discovery process is relevant to academics, financial market regulators, and practitioners. Second, we investigate how the practices of short selling and margin trading influence the distributional characteristics of returns on the affected securities. These characteristics include skewness, kurtosis, and the occurrence of extreme negative and positive returns. Hong and Stein's (2003) model suggests severe price drops when unrevealed information due to shorting restrictions becomes public in down markets. The theoretical model of Xu (2007) predicts that differences in investors' opinions and short sale constraints increase the skewness of stock returns. Therefore, it is interesting to investigate the theoretical implications of the models in Hong and Stein (2003) and Xu (2007) for an emerging market. Previous studies, such as Brown and Mitchell (2008), show that Chinese investors view the number 8 as "lucky" and the number 4 as "unlucky", and this manifests itself in more prices ending in 8 than 4. Our third contribution is examining whether cultural price clustering decreases following the introduction of regulation that is intended to improve price discovery. Our analysis benefits from the regulatory feature of the Chinese market where short selling and margin trading have been partially allowed in two phases for a large group of securities.

A number of studies examine the introduction of short selling and margin trading in China from different perspectives. Sharif *et al.* (2014a, b) and Wang (2012) find a decline in the prices or returns on stocks subject to the regulatory change relative to matched firms. Sharif *et al.* (2014a, b) also show that there are liquidity declines in affected stocks. Wang

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1 See, for example, Bris *et al.* (2007) and Saffi and Sigurdsson (2011).

2 See, for example, http://us.practicallaw.com/5-517-6421?source=relatedcontent#a454418.

3 The 287 securities eligible for margin trading and short selling from December 2011 consist of Shanghai Stock Exchange SSE-180 index stocks, Shenzhen Stock Exchange SZSE-100 index stocks, and seven exchange-traded funds (ETFs), among which four are listed on the SSE and three on the SZSE.

(2011) shows an increase in informed trading when investors are allowed to trade on margin.[4]

Our paper contributes to the important work of Bris *et al.* (2007) and Saffi and Sigurdsson (2011). Bris *et al.* (2007) analyse the effects of short sale constraints on market efficiency in 46 countries and find that stocks are more efficiently priced in countries where short selling is practicable and less constrained. Saffi and Sigurdsson (2011) also conclude, on the basis of firm-level data from 26 countries, that stock prices are more efficient where short sale constraints are low. Our single-country analysis differs from these studies as we use actual short selling and margin buying data to directly examine the impact of short selling on information efficiency measures.[5] Prior to the approval of short selling and its subsequent expansion, put options were non-existent in China, which suggests that negative information could not be incorporated easily into stock prices before the change in regulations. Bris *et al.* (2007) use country-level short sale constraints data, whereas Saffi and Sigurdsson (2011) use short sale constraint proxies to examine their impact on prices.

There is no consistent change in information efficiency across the different measures we employ following the commencement of short selling and margin trading. We find mixed results for R^2s, suggesting that efficiency has slightly improved for affected securities with higher short sales. However, we find mixed results for another efficiency measure: cross-autocorrelation (ρ). We also estimate two measures of price delay proposed by Hou and Moskowitz (2005) from market model regressions. The first delay measure (*D1*) compares the fraction of changes in stock returns arising from lagged market returns. The second delay measure (*D2*) tests the size of the lagged market return betas relative to the contemporaneous market return beta. Lower values of *D1* and *D2* suggest that the speed of price adjustment is faster. Both delay measures are insignificantly different from zero following the inception of short selling and margin trading. Moreover, we run some robustness tests on weekly data[6] one year before and after the change in policy. Overall, we find an improvement in price discovery to a certain extent, and our mixed evidence could be attributed to the simultaneous introduction of securities lending and margin borrowing.

At the same time, we find a significant decline in the positive skewness of affected securities' abnormal returns following the removal of constraints on short selling and margin trading. This reduction in skewness is observed for firms with higher short selling activities, consistent with the theoretical model proposed by Xu (2007). The occurrence of extreme

[4] We have become aware of findings by Chang *et al.* (2012), who examine the impact of the relaxation of short selling and margin trading constraints on pricing efficiency and stock return distributions in China. They also find no improvement in information efficiency following the practice of short selling and margin trading.

[5] Cheng *et al.* (2012) also examine the effects of short selling on IPO information efficiency in Taiwan six months before and after the relaxation of short sale constraints using actual short selling data.

[6] Bris *et al.* (2007) believe that daily data carry too much noise. This might have implications for our results; hence, robustness tests are conducted on weekly data.

positive returns increases significantly in the post-period for securities with higher short selling and margin trading activities. This result most likely suggests that the lifting of short sale restrictions does not cause extreme negative returns, and/or margin buyers dominate the market compared to short sellers. Lastly, we find a significant increase in daily closing prices ending with the digit 4 as compared to the digit 8 following the implementation of short selling and margin trading. The variation in price clustering considerably reduces through changes in the relative frequencies of end digits 0 to 9 in all daily prices following the introduction of short selling and margin trading. This suggests that the policy shift has resulted in some reduction of the influence of cultural superstitions on prices.

The remainder of the paper is organised as follows: Section II presents the literature review and develops the hypotheses, section III describes the data and sample, section IV explains the methodology used, section V presents our results, and section VI concludes the paper.

II. Literature Review and Hypotheses Development

The majority of studies find that prices are more efficient when short selling is allowed. Bris *et al.* (2007) conclude this after studying short sale regulations from 46 countries, and Saffi and Sigurdsson (2011) reach a similar conclusion after studying 26 countries. Cheng *et al.* (2012) find a positive relationship between information efficiency and short selling activities for newly listed Taiwanese stocks. Moreover, Seguin (1990) examines the introduction of margin buying for OTC stocks in the US and finds lower volatility and an improvement in price informativeness for stocks eligible for margin trading. Hence, based on the literature discussed above, our first hypothesis is as follows:

Hypothesis 1: The speed of adjustment and the efficiency of security prices improve following the lifting of short selling and margin trading constraints.

There is no consensus in the literature on the association between short sale constraints and the positive or negative skewness of stock returns. The theoretical model of Xu (2007) predicts that divergence in investors' opinions and short sale constraints increase the skewness of stock returns. Consistent with this proposition, Chang *et al.* (2007) and Saffi and Sigurdsson (2011) find a decline in the skewness of returns when short selling constraints are relaxed. However, evidence from Bris *et al.* (2007) is inconsistent with the implication of Xu's (2007) paradigm; they find less negative skewness in markets where short selling is not practicable. Charoenrook and Daouk (2005) find no evidence of short sale constraints affecting the level of market return skewness. Further, the individual stock returns are generally positively skewed (Xu, 2007). Hence, given the above literature, we propose our second hypothesis that following the lifting of short sale restrictions in China, security prices incorporate adverse information faster and thus the probability of observing negative (positive) skewness in returns increases (decreases):

Hypothesis 2: The negative skewness of security returns increases and/or the positive skewness of security returns decreases following the lifting of short selling and margin trading constraints.

The magnitude and probability of observing extreme price movements following short selling and margin borrowing activities can be gauged from the kurtosis of returns and extreme positive and negative returns. There is no consensus in the literature on the relationship between short sale constraints and the occurence of extreme returns. Thicker tails in the distribution of returns indicate high kurtosis, which would imply a higher frequency of extreme returns. Saffi and Sigurdsson (2011) find smaller kurtosis and a lower frequency of extreme positive returns for individual stocks with less short sale restrictions. This finding is consistent with the implication of Hong and Stein's (2003) model that suggests more extreme negative returns in the presence of short sale constraints. Hong and Stein's model argues that in the presence of short selling constraints, the unrevealed adverse information possessed by short sellers becomes noticeable in declining markets and this further intensifies the market declines. However, Bris *et al.* (2007) find that allowing short selling increases the likelihood of crashes, which is in accordance with the general opinion of financial regulators that restricting short selling decreases the frequency of extreme negative returns. Similarly, Chang *et al.* (2007) find an increase in the occurrence of extreme negative stock returns following the relaxation of short sale constraints in Hong Kong. On the other hand, Charoenrook and Daouk (2005) find no evidence that short selling affects the probability of extreme negative market returns. Thus, based on the mixed evidence above, our third and fourth hypotheses are as follows:

Hypothesis 3: The kurtosis of security returns does not change following the lifting of short selling and margin trading constraints.

Hypothesis 4: The occurrence of extreme negative and positive returns does not change following the lifting of short selling and margin trading constraints.

Ball *et al.* (1985) hypothesise that price clustering is a function of uncertainity about the value of an asset. The price clustering is high when the fair price of an asset is not fully known. Chinese investors prefer the number 8, which is considered "lucky", and avoid the number 4, which is considered "unlucky", in their investment decisions (Brown and Mitchell, 2008). Bhattacharya *et al.* (2017) find that individual investors, but not institutional investors, submit disproportionately more limit orders at prices ending in 8 rather than ending in 4 in the Taiwanese stock market. However, the frequency of individuals submitting orders at prices ending in 8 rather than ending in 4 decreases with trading experience. Likewise, Aitken *et al.* (1996) suggest that price clustering decreases when the price discovery improves through options trading and short selling. Hence, based on the literature discussed above, our fifth hypothesis is as follows:

Hypothesis 5: The price clustering in equity prices based on cultural bias for certain numbers reduces following the lifting of short selling and margin trading constraints.

III. Data and Sample

Data on daily stock returns, prices, trading volumes, shares outstanding, and value-weighted indices' returns are obtained from the Thomson Reuters Datastream (TRD) database. The daily short sales and margin trading data are obtained from the China Securities Market and Accounting Research (CSMAR) database. The sample covers the period from 1 June 2009 to 30 June 2012.[7] During the sample period, there are 285 A-shares and seven exchange-traded funds (ETFs) commencing short sales and margin trading at the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). Under the pilot programme, short selling and margin buying were allowed for 90 stocks from 31 March 2010. Following the adjustment/reconstitution of the SSE-50 and SZSE-40 indices, five more stocks became eligible for short selling and margin trading from 1 July 2010. Finally, on 5 December 2011 when the pilot programme was converted to regular business, 190 additional stocks and seven ETFs were included in the list.

We use daily data to examine the information efficiency measures, the characteristics of stock return distributions, and the price clustering. We apply a filter of at least 100 daily observations, before and after the introduction of short sales and margin trading, which reduces our final sample down to 277 A-shares and seven ETFs. Out of the total sample, 180 A-shares and four ETFs are listed on the SSE, whereas 97 A-shares and three ETFs are listed on the SZSE. The pre-period is seven months before the commencement of short selling and margin trading for each stock,[8] whereas the post-period is seven months immediately following the launch of short sales and margin trading for each stock. Figure 1 shows the timeline of the pre- and post-periods.

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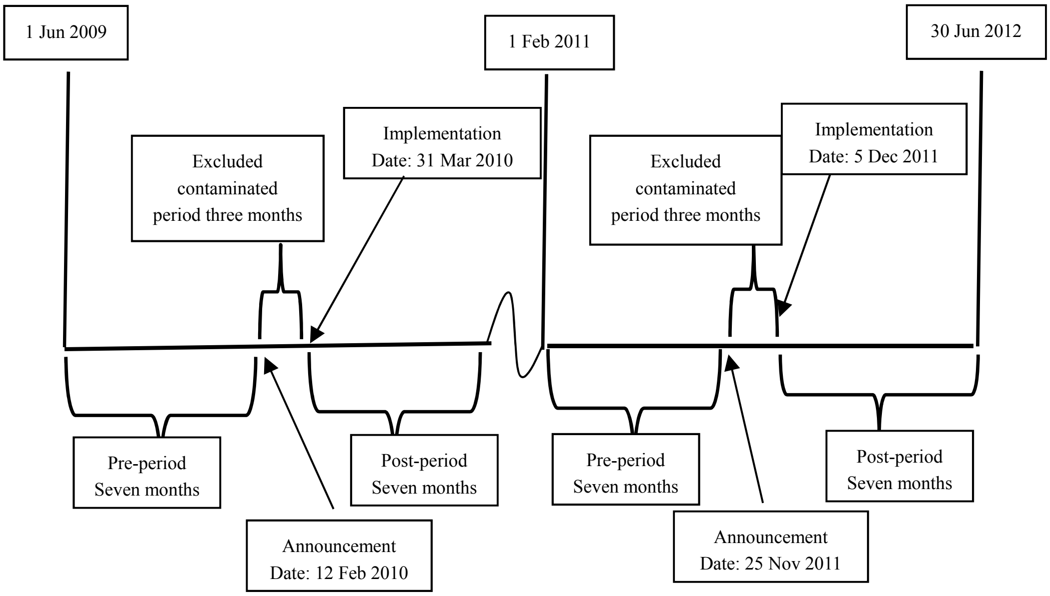
[7] For the robustness tests, we use weekly data for 90 affected stocks from the first phase of the regulatory change and 90 non-affected stocks. The pre-period is from January 2009 to December 2009, and the post-period is from April 2010 to March 2011. A filter of at least 40 weekly observations is applied for each stock before and after the policy shift.

[8] In order to avoid any contaminating effect of the announcement of stocks eligible for short sales and margin trading, we take a seven-month period that is three months prior to the commencement of short selling and margin trading as our pre-period. For example, if the sample stock is eligible for short selling and margin trading from 5 December 2011, then the pre-period is from 1 February 2011 to 31 August 2011. A similar treatment is done while downloading the weekly data: that is, the pre-period is the one-year period that is three months prior to the enforcement of the pilot programme (i.e. from January to December 2009).

Figure 1 Pre- and Post-Period Timelines for Short Selling and Margin Trading[9]



IV. Methodology

4.1 Measures of Information Efficiency

First, we employ R^2 to examine whether the price discovery improves following the relaxation of constraints on short sales and margin buying. Roll (1988) suggests that if investors' trading is linked with more firm-related information, this leads to higher stock return variation and hence lowers the security's R^2.[10] Second, we employ cross-autocorrelation: lower cross-autocorrelation indicates greater speed of price adjustment. Third, we employ two price delay measures: lower delay measures suggest higher efficiency.

To measure the pricing efficiency, we follow Bris *et al.* (2007) to calculate the R^2, upside R^2, and downside R^2 from the following three regressions:

$$r_{it} = \alpha_i + \beta_i^M * r_{mt} + \varepsilon_{it}, \quad (1)$$

where we regress daily stock returns on the value-weighted market return for firm *i* and in day *t*;

$$r_{it} = \alpha_i + \beta_i^M * r_{mt}^{+} + \varepsilon_{it}, \quad (2)$$

[9] Five A-shares were allowed for short selling and margin buying from 1 July 2010 due to adjustment of the SSE-50 Index and the SZSE Component (40) Index. The pre-period for those stocks is from 1 September 2009 to 31 March 2010, and the post-period is between 1 July 2010 and 31 January 2011.

[10] Since the R-Squared measure is determined by both the amount of firm-specific information and the level of sentiment driven by trading (e.g. Hou *et al.*, 2006; Teoh *et al.*, 2009), and some researchers have argued about the power of R-Squared as a proxy (Li et al., 2014), we use the phrase "information efficiency" rather than price efficiency, as suggested by Zhang *et al.* (2016).

where r_{mt}^{+} equals the market return when it is either positive or zero;

$$r_{it} = \alpha_i + \beta_i^M * r_{mt}^{-} + \varepsilon_{it}, \tag{3}$$

where r_{mt}^{-} equals the market return when it is negative.

Similarly, following Bris *et al.* (2007), we measure asymmetries by computing the difference between downside and upside R^2. All confounding factors that impact both the upside and the downside portions of idiosyncratic risk are considered in the downside-minus-upside R^2.

Next, we estimate an alternative proxy for pricing efficiency by computing cross-autocorrelations between market returns lagged one day and individual stock returns. Again, following Bris *et al.* (2007), we calculate $\rho_{it}^{+} = corr(r_{it}, r_{mt-1}^{+})$ and $\rho_{it}^{-} = corr(r_{it}, r_{mt-1}^{-})$ for affected securities using daily observations. We then average the cross-autocorrelations across stocks and calculate the difference:

$$\rho_i^{Diff} = \rho_i^{-} - \rho_i^{+}. \tag{4}$$

To examine the changes in information efficiency measures following the introduction of short sales and margin trading activities, we conduct the *t*-test and Wilcoxon rank sum test for the pre-period and post-period paired samples.

Moreover, to measure the speed of information diffusion in prices, we compute two stock price delay measures developed by Hou and Moskowitz (2005). The market return is employed as a proxy for new information to which individual stock prices react:

$$r_{i,t} = \alpha_i + \beta_i^0 R_{m,t} + \varepsilon_{i,t} \qquad \text{(Base market model)} \tag{5}$$

$$r_{i,t} = \alpha_i + \beta_i^0 R_{m,t} + \sum_{n=1}^{4} \beta_i^n R_{m,-n} + \varepsilon_{it}, \qquad \text{(Extended market model)} \tag{6}$$

where $r_{i,t}$ is the return on stock *i* for day *t*; $R_{m,t}$ ($R_{m,-n}$) is the value-weighted market index return (four-day lagged returns on the market portfolio). In Equation (6), if the stock reacts immediately to new information, β_i^0 will be significantly different from zero but the coefficients β_i^n will not differ significantly from zero. Alternatively, if the reaction is delayed, β_i^0 will be less significant or insignificant and some or all of the β_i^ns will be significantly different from zero.

We also use two price delay measures to test the efficiency, consistent with Hou and Moskowitz (2005) and Saffi and Sigurdsson (2011). The first R^2 ratio measures the proportional difference between the explanatory power of contemporaneous versus lagged market returns to predict stock returns.

$$D1_i = 1 - \frac{R_{base}^2}{R_{extended}^2}, \tag{7}$$

where R^2s are obtained from equations (5) and (6) from the base and the extended market models, respectively. The larger the *D1*, the higher the variation in stock returns captured by the lagged market returns, which implies a longer price delay or a slower speed with which stocks respond to relevant information. However, *D1* does not take the magnitude of the coefficients of lagged market returns into account (i.e. *D1* does not distinguish between shorter and longer lags or the precision of the estimates). Therefore, another delay measure is developed as follows:

$$D2_i = \frac{\sum_{n=1}^{5} abs(\beta_i^n(-n))}{abs(\beta_i^0)+\sum_{n=1}^{5} abs(\beta_i^n(-n))} \tag{8}$$

This measure captures the magnitude of the lagged coefficients relative to the magnitude of all market return coefficients.

4.2 Price Clustering

To test Hypothesis 5 on the cultural influences on stock price clustering, we measure the frequencies of all prices ending with the digits 0 to 9 observed during the pre- and post-periods (i.e. the second decimal place of daily opening, high, low, and closing prices). Following Brown and Mitchell (2008), we compare the daily frequencies of (i) 2 with 8, (ii) 4 with 6 (all are even numbers and equidistant from 0 to 5), and (iii) 4 with 8. The third comparison of frequency of 4 with 8 specifically predicts the Chinese cultural effects (4 is less prevalent than 8), which is in contrast to the first two comparisons. In the absence of price clustering, the above ratios would be close to 1. We test the clustering effect using seven-month daily data in each pre- and post-period for all affected securities.

V. Empirical Results

5.1 Efficiency Measures

To observe how the lifting of short selling and margin buying restrictions impacts the pricing efficiency measures, we first look at the univariate results.

5.1.1 Univariate Analysis

The cross-sectional averages are reported in Table 1. We find that R^2 increases significantly following the inception of short sales and margin buying, suggesting that information efficiency has not improved in the post-period.[11] When we decompose the R^2 into the downside R^2 and upside R^2, depending on the negative and positive market returns, respectively, the downside R^2 does not change, whereas the upside R^2 increases significantly, indicating lower information efficiency in the post-period. Next, our second efficiency measure, the cross-autocorrelation (ρ), exhibits a significant decline in price delay. Similarly, the decline is significant for the downside cross-autocorrelation (ρ_{it}^{-}) in the post-period.[12]

[11] We also transform R^2 into a continuous variable ranging between -∞ and +∞, as applied by Bris *et al.* (2007), but the significance level of our univariate and multivariate results does not change if we apply the transformation.

[12] Similarly, we transform ρ to take the values between -∞ and +∞, as applied by Bris *et al.* (2007), but the results are similar after the transformation.

The lower value of the ρ_{it}^{-} measure suggests that individual stock returns adjust faster in a falling market following the regulatory change. However, the upside ρ increases in the post-period, suggesting lower information efficiency in a bullish market. Further, when short selling and margin trading are allowed in the post-period, we find significantly lower downside-minus-upside R^2 and downside-minus-upside ρ. This evidence is consistent with the argument that relaxing short sale constraints facilitates price discovery, conditional on a negative market return. In addition, the two price delay measures *D1* and *D2* show lower values in the post-period but are not significantly different from zero. The lower values of *D1* and *D2* imply a lower price delay (or faster speed) in incorporating new market information. Overall, the results from Table 1 suggest that there is no consistent pattern of changes in efficiency across the different measures following the inception of short sales and margin trading. In sum, the findings based on univariate analysis appear to be mixed for our first proposed hypothesis.

Table 1 Univariate Analysis - Changes in Information Efficiency Measures

This table reports the cross-sectional average of the estimated measures of information efficiency. The columns labelled 'Pre' show the cross-sectional mean and median of each measure for the seven months before the inception of short selling and margin trading. The columns labelled 'Post' show the average of variables during the seven months following the introduction. A minimum of at least 100 trading days is required for both the pre- and post-periods. A paired t-test and the Wilcoxon non-parametric test are used to analyse the difference between the two periods. Also reported are the 'Diff' of Post minus Pre and associated p-values.

	Mean				Median			
	All Securities (N = 284)							
	Pre	Post	Diff	p-value	Pre	Post	Diff	p-value
R-Squared	0.4307	0.5029	0.0722	0.0001	0.4250	0.5111	0.0861	0.0001
Downside minus Upside *R*-Squared	0.1019	-0.0401	-0.1420	0.0001	0.0879	-0.0417	-0.1295	0.0001
Upside *R*-Squared	0.2146	0.3617	0.1472	0.0001	0.1797	0.3513	0.1716	0.0001
Downside *R*-Squared	0.3165	0.3217	0.0052	0.7253	0.2904	0.3076	0.0172	0.4221
Cross-autocorrelation	0.0208	0.0057	-0.0151	0.0245	0.0206	0.0172	-0.0034	0.1295
Downside minus Upside Cross-autocorrelation	0.1203	0.0574	-0.0629	0.0001	0.1138	0.0587	-0.0550	0.0001
Upside Cross-autocorrelation	-0.0584	-0.0308	0.0276	0.0112	-0.0637	-0.0347	0.0289	0.0194
Downside Cross-autocorrelation	0.0620	0.0266	-0.0354	0.0022	0.0619	0.0296	-0.0323	0.0031
D1	0.0501	0.0467	-0.0035	0.4744	0.0317	0.0318	0.0001	0.3970
D2	0.2458	0.2365	-0.0093	0.2723	0.2337	0.2281	-0.0056	0.3426

5.1.2 Robustness Check

For a robustness check, a univariate analysis is conducted on weekly returns following Chang *et al.* (2014), since the daily return data carry noise trading (e.g. Bris *et al.*, 2007). For the purpose of this analysis, 90 affected stocks (i.e. eligible under phase I of the pilot programme) are taken, and as a control group, 90 non-affected stocks (i.e. stocks that were not part of the pilot programme) are considered.[13,14] The weekly data for the pre-period are from January to December 2009 and for the post-period are from April 2010 to March 2011. The results for the three main efficiency measures (i.e. R^2, cross-autocorrelation, and price delay measure *D1*) are reported in the Appendix. Interestingly, we observe that R^2 and *D1* have significantly declined in the post-period at the 10% and 5% levels, respectively, following the introduction of the pilot programme, suggesting that the change in policy has slightly improved the information efficiency environment for the pilot securities. However, the non-parametric median p-values do not show significant results.

5.1.3 Multivariate Analysis

To test Hypothesis 1, we estimate a number of regression models to examine how the dependent variable of efficiency changes following the relaxation of constraints on short sales and margin borrowing. We estimate the following model/Equation (9) using the ordinary least squares regression method. The data are analysed for the seven-month post-period window:

$$R_i^2 = \alpha_0 + \alpha_1 SS\_Ratio_i + \alpha_2 MT\_Ratio_i + Control\ Variables + \varepsilon_{i,t}, \quad (9)$$

where the dependent variables are R-Squared, R-Squared Difference, Downside R-Squared, and Upside R-Squared, as discussed in the methodology section, for each regression model. The independent variables are as follows: *SS_Ratio* is the average of daily short sales volume divided by daily trading volume, and *MT_Ratio* is the average of daily margin volume divided by daily trading volume. The control variables are as follows: *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise; the percent of zero returns is the average number of days a stock has a zero return divided by the total number of trading days in the seven-month post-period with available return data. The regression results for R^2 are reported in Table 2. Consistent with our univariate results, we observe a significantly positive coefficient on *SS_Ratio* (daily short sales volume divided by total volume), implying that short selling does not facilitate efficiency. The increase in R^2 measure following the regulatory change is a counter to the evidence of Bris *et al.* (2007). Following Bris *et al.* (2007), we decompose R^2 into upside and downside market movements. Downside R^2 shows a significantly positive coefficient with *SS_Ratio* and a significantly negative coefficient with *MT_Ratio* (daily margin buying volume divided by total volume). Similarly, Upside R^2 shows a positively significant coefficient with *SS_Ratio*. However, the effect of short selling and margin trading on the downside-minus-upside R^2 is negative and statistically significant at

[13] The 90 non-affected stocks are matched with pilot stocks from the same industry on the four factors: mean market value of equity (i.e. size), closing price, volatility of daily returns, and daily turnover between 1 October 2008 and 30 September 2009. This gives us unique combinations of a peer firm for each affected firm. This matching methodology to draw a control group of firms follows Sharif *et al.* (2014a).

[14] A similar approach is also adopted by Xu and Chen (2012) and Wang (2015).

the 1% level, suggesting that the price discovery process relatively improves when the market is going down.[15] Overall, the results for R^2s seem to be mixed with regard to Hypothesis 1 and the broad literature, such as the finding of Bris *et al.* (2007) that allowing short selling facilitates market efficiency.

Table 2 Cross-Sectional Regressions of R-Squared

For each security in our sample, we calculate the R^2 from regressions of individual stock returns on the value-weighted domestic market index returns. The estimation period of R^2s is the daily data of the seven-month post-period market-model regression analysis for affected securities. We use either negative or positive market returns to calculate downside-R^2 or upside R^2. We also compute the difference for downside-R^2 minus upside-R^2. *SS_Ratio* is the average of daily short sales volume divided by daily trading volume. *MT_Ratio* is the average of daily margin volume divided by daily trading volume. *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise. The percent of zero returns is the average number of days a stock has a zero return, divided by the total number of days in the seven-month period with available return data.

	Exp. Sign	*R*-Squared	*R*-Squared Difference Downside Minus Upside	Downside *R*-Squared	Upside *R*-Squared
		(I)	(II)	(III)	(IV)
SS_Ratio	−	0.0070***	-0.0074***	0.0049***	0.0123***
		(3.96)	(-4.69)	(2.71)	(6.62)
MT_Ratio	−/+	-0.0002	-0.0010***	-0.0007***	0.0003
		(-0.97)	(-4.20)	(-2.70)	(0.97)
Cross-List	−/+	0.0767***	0.0450*	0.0883***	0.0433
		(2.98)	(1.92)	(3.33)	(1.58)
Days with zero return (%)	−	-0.4415***	-0.0912	-0.2863*	-0.1951
		(-2.69)	(-0.61)	(-1.70)	(-1.12)
Constant		0.4937***	0.0273*	0.3285***	0.3012***
		(27.23)	(1.66)	(17.62)	(15.61)
Obs.		284	284	284	284
Adj. R^2		0.0829	0.1776	0.0682	0.1517

Besides examining the marginal impact of increased short sales on the securities' efficiency measure, this study conducts two regression analyses as a robustness check. The first regression uses a dummy indicator of the pre- and post-event trading periods on weekly data (post-period = 1; 0 otherwise), and the second regression uses a dummy indicator for securities being included in the pilot programme or not (eligible stocks = 1; 0 otherwise). The dependent variable of efficiency is R^2, and the results are reported in Table 2-A. Somewhat consistent with the univariate results on weekly data, we find a significant improvement in information efficiency for the post-event period, with the period dummy showing a negative coefficient at the 1% level. The decline in R^2 suggests that the

[15] Although the coefficient on *SS_Ratio* is significantly positive for both downside and upside R^2, the magnitude and t-value of downside R^2 are much smaller than those of upside R^2.

informational environment has improved. However, the second model shows that the R^2 coefficient is not different from zero. Therefore, the evidence shows some degree of efficiency after margin trading and short sales are allowed in China. This could be a consequence of the simultaneous implementation of both margin buying and securities lending (e.g. Chu and Fang, 2016), whereby short sellers drive affected stock prices down and this effect is mitigated by margin buyers.

Table 2-A Cross-Sectional Regressions of R-Squared

For each security in our sample, we calculate the R^2 from regressions of individual stock returns on the domestic market index. The estimated R^2 for individual stocks are obtained from the weekly market-model regression results. In the first model, the independent variable is a dummy indicator for the pre- and post-event trading for 90 stocks eligible in the programme. In the second model, the independent variable is a dummy indicator for 90 eligible stocks and 90 non-eligible stocks. *, **, and *** show significance at the 10%, 5%, and 1% levels, respectively.

	Exp. Sign	*R*-Squared	*R*-Squared
		(I)	(II)
Period_Dummy	−	-0.0964***	
		(-3.89)	
Eligibility_Dummy	−		0.0139
			(0.50)
Constant		0.5205***	0.4101***
		(29.76)	(20.78)
Obs.		180	180
Adj. R^2		0.0735	0.0014

To examine Hypothesis 1, the next dependent variable is our second measure of price efficiency: the cross-autocorrelation (ρ) between one-day lagged market return and individual stock return. The estimated OLS regression model is similar to Equation (9), except that the dependent variables are Cross-autocorrelation, Downside-minus-Upside cross-correlation, Downside correlation, and Upside correlation. The explanatory variables are *SS_Ratio*, *MT_Ratio*, the cross-list dummy, and percentage of zero-return days. In Table 3, the first column shows the results for cross-autocorrelation, the second column the results for the downside-minus-upside cross-autocorrelation, and the last two columns the results for the downside and the upside cross-autocorrelation separately. The speed of price adjustment measured by the cross-autocorrelation is not associated with short selling or margin trading (column I). When we decompose the cross-autocorrelation on the basis of the direction of market movements, surprisingly, we find that short selling is related to a reduction in the upside cross-autocorrelation (column IV). This suggests that the speed of price adjustment is faster in an up market for securities with higher short sales. In addition, we find a significant increase in the downside cross-autocorrelation for firms with a higher margin trading volume (column III). Overall, the multivariate results for our second measure of efficiency show a certain level of improvement and loosely confirm Hypothesis 1 and the finding in the broad literature, such as Saffi and Sigurdsson (2011), that fewer short sale constraints allow faster incorporation of bad news into prices.

Table 3 Cross-Sectional Regressions of Cross-Autocorrelation

For each security, we calculate cross-autocorrelations between one-day lagged market returns and individual stock returns. Downside cross-autocorrelation between the stock return and the lagged market return is computed when the market is negative using daily observations in each seven-month post-period, and Upside cross-autocorrelation between the stock return and the lagged market return is computed when the market is positive. We then calculate the difference downside-minus-upside cross-autocorrelation. *SS_Ratio* is the average of daily short sales volume divided by daily trading volume. *MT_Ratio* is the average of daily margin volume divided by daily trading volume. *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise. The percent of zero returns is the average number of days a stock has a zero return, divided by the total number of trading days in the seven-month post-period with available return data.

	Exp. Sign	Cross-Autocorrelation	Downside Minus Upside Cross-Autocorrelation	Downside Cross-Autocorrelation	Upside Cross-Autocorrelation
		(I)	(II)	(III)	(IV)
SS_Ratio	−	-0.0011	0.0038*	0.0004	-0.0035**
		(-1.10)	(1.90)	(0.24)	(-2.13)
MT_Ratio	−/+	0.0002	0.0014***	0.0012***	-0.0002
		(1.25)	(4.77)	(5.64)	(-0.70)
Cross-List	−/+	-0.0472	-0.1140***	-0.0907***	0.0233
		(-3.20)	(-3.83)	(-4.09)	(0.97)
Weeks with zero return (%)	−/+	-0.0868	0.0689	0.0185	-0.0504
		(-0.92)	(0.36)	(0.13)	(-0.33)
Constant		0.0158	0.0017	-0.0082	-0.0100
		(1.52)	(0.08)	(-0.53)	(-0.59)
Obs.		284	284	284	284
Adj. R^2		0.0350	0.1615	0.1687	0.0154

Similarly, we conduct two regressions as robustness checks. The first regression uses a dummy indicator of the pre- and post-event trading periods on weekly data (post-period = 1; 0 otherwise), and the second regression uses a dummy indicator for securities being included in the pilot programme or not (eligible stocks = 1; 0 otherwise). The dependent variable of efficiency taken here is Cross-autocorrelation, and the results are reported in Table 3-A. Consistent with the univariate results based on weekly data, we find no change in the price efficiency proxy for both models. The likely reason for this finding is that the policy shift in the Chinese market allows both short sellers and margin buyers to trade (e.g. Chu and Fang, 2016); therefore, we do not observe any change in the pricing efficiency proxy.

Table 3-A Cross-Sectional Regressions of Cross-Autocorrelation

For each security in our sample, we calculate the cross-autocorrelation between individual stock returns and the lagged value-weighted domestic market index returns. The cross-autocorrelations for individual stocks are calculated on the weekly returns. In the first model, the independent variable is a dummy indicator for the pre- and post-event trading for 90 stocks eligible in the programme. In the second model, the independent variable is a dummy indicator for 90 eligible stocks and 90 non-eligible stocks. *, **, and *** show significance at the 10%, 5%, and 1% levels, respectively.

	Exp. Sign	Cross-Autocorrelation	Cross-Autocorrelation
		(I)	(II)
Period_Dummy	−	0.0149	
		(0.89)	
Eligibility_Dummy	−		-0.0092
			(-0.59)
Constant		-0.0253**	-0.0010
		(-2.12)	(-0.09)
Obs.		180	180
Adj. R^2		0.0044	0.0019

Table 4 Cross-Sectional Regressions of Price Delay Measures

For each security, we calculate *D1* and *D2*, which are proxies for price delay, as in Hou and Moskowitz (2005). *D1* and *D2* are computed from the daily data of the seven-month post-period regression analysis. *SS_Ratio* is the average of daily short sales volume divided by daily trading volume. *MT_Ratio* is the average of daily margin volume divided by daily trading volume. *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise. The percent of zero returns is the average number of days a stock has a zero return, divided by the total number of days in the seven-month period with available return data. Market Cap is market capitalisation. Turnover is total volume traded to shares outstanding. Bid-Ask is the closing spread scaled by price. *, **, and *** show significance at the 10%, 5%, and 1% levels, respectively.

	Exp. Sign	*D1*	*D2*
		(I)	(II)
SS_Ratio	−	-0.0007	-0.0018
		(-1.12)	(-1.59)
MT_Ratio	−/+	-0.0002	-0.0002
		(-1.47)	(-1.20)
Cross-List	−/+	-0.0076	-0.0187
		(-0.78)	(-1.06)
Market Cap	−	-0.0000	-0.0000
		(-0.29)	(-0.53)
Turnover	−	1.3353***	0.9774
		(3.62)	(1.46)
Days with zero return (%)	−/+	0.1303**	0.1433
		(2.25)	(1.36)
Bid-Ask	−/+	3.1020	4.5174
		(0.81)	(0.65)
Constant		0.0324***	0.2339***
		(3.75)	(14.90)
Obs.		284	284
Adj. R^2		0.0621	0.0151

Finally, following Hou and Moskowitz's (2005) methodology, we use two price delay measures, *D1* and *D2*, as dependent variables to test the effect of short sales and margin buying on the speed of information diffusion. The estimated OLS regression model is similar to Equation (9), except that the dependent variables are *D1* and *D2*. Higher values of *D1* and *D2* suggest lower efficiency and greater price delay. In columns I and II of Table 4, we observe negative but insignificant coefficients for the ratios of short selling and margin trading, suggesting that *D1* and *D2* are very weakly associated with short selling and margin trading activities; hence, affected securities depict only some degree of reduction in price delay. Consistent with prior literature, we observe a positive coefficient for less liquid stocks (column I), and we find a significantly positive relationship between *D1* and turnover, which is somewhat puzzling.

Again, we perform two regression analyses as robustness checks. The first regression uses a dummy indicator of the pre- and post-event trading periods on weekly data (post-period = 1; 0 otherwise), and the second regression uses a dummy indicator for securities being included in the pilot programme or not (eligible stocks = 1; 0 otherwise). The dependent variable of efficiency is the price delay measure *D1* (lower delay measure suggests better efficiency), and the results are reported in Table 4-A. Again consistent with the univariate results on weekly data, we find a weakly significant improvement in information efficiency for the post-event period, with the period-dummy showing a negative coefficient at the 10% level. The decline in *D1* suggests that the informational environment has somewhat improved. However, the coefficient of *D1* in the second model is not different from zero. Therefore, on the whole, allowing margin trading and short selling has facilitated market efficiency in China to a limited extent. Again, the mixed findings could emanate from the presence of both short sellers and margin buyers in China (e.g. Xu and Chen, 2012).

Table 4-A Cross-Sectional Regressions of Price Delay Measure

For each security in our sample, we calculate *D1* and *D2*, which are proxies for price delay, as in Hou and Moskowitz (2005). *D1* and *D2* are computed from the regression analysis on weekly data for one year before and after the regulatory change. In the first model, the independent variable is a dummy indicator for the pre- and post-event trading for 90 stocks eligible in the programme. In the second model, the independent variable is a dummy indicator for 90 eligible stocks and 90 non-eligible stocks. *, **, and *** show significance at the 10%, 5%, and 1% levels, respectively.

	Exp. Sign	*D1*	*D1*
		(I)	(II)
Period_Dummy	−	-0.0462*	
		(-1.89)	
Eligibility_Dummy	−		0.0139
			(0.52)
Constant		0.5212***	0.4612***
		(30.25)	(24.65)
Obs.		180	180
Adj. R^2		0.0143	0.0015

Taken together, the evidence with different measures of efficiency appears to be mixed against the proposed Hypothesis 1 that relaxing the short selling and margin trading constraints makes markets more efficient. These results are more likely to imply that the distributions of daily returns may not closely follow a random walk after short selling and margin buying was permitted; these distributions are examined in the next section.

5.2 Distributional Characteristics of Stock Returns

5.2.1 Univariate Analysis

We now investigate how short selling and margin trading activities affect the distributional characteristics of stock returns. The results are reported in Table 5. The abnormal returns are the residuals of the market model regression for each firm in the post-event period (i.e. following the change in policy). After the removal of short sale and margin trading constraints, there is a significant decline in mean raw returns and the volatility of abnormal returns, a reduction in positive skewness of abnormal returns, and an increase in extreme positive stock returns. Lower volatility is consistent with the findings of

Table 5 Univariate Analysis – Changes in the Characteristics of Stock Returns Distributions

This table reports the characteristics of stock return distributions. The abnormal returns are the residuals from a regression of stock returns on the market index (market model) for each firm in the seven-month pre-period and post-period (i.e. following the change in regulations). The columns labelled ‘Pre’ show the cross-sectional mean and median of each characteristic for the seven months before the inception of short selling and margin trading. The columns labelled ‘Post’ show the average of variables during the seven months following the introduction. A minimum of at least 100 trading days is required for both the pre- and post-periods. The paired *t*-test and the Wilcoxon non-parametric test are used to analyse the difference between the two periods. Also reported are the ‘Diff’ of Post minus Pre and associated p-values.

All Stocks (N=284)		Mean				Median			
		Pre	Post	Diff	p-value	Pre	Post	Diff	p-value
Mean	Raw Returns	0.0000	-0.0006	-0.0006	0.0001	-0.0001	-0.0006	-0.0005	0.0001
Standard Deviation	Raw Returns	0.0242	0.0234	-0.0009	0.0717	0.0234	0.0235	0.0001	0.3372
	Abnormal Returns	1.0470	0.9490	-0.0980	0.0001	1.0556	0.9552	-0.1004	0.0001
Skewness	Raw Returns	0.0434	0.0667	0.0232	0.5475	0.0434	0.0494	0.0060	0.3552
	Abnormal Returns	0.7573	0.4376	-0.3196	0.0001	0.7818	0.4560	-0.3258	0.0001
Kurtosis	Raw Returns	1.9074	1.5615	-0.3459	0.0515	1.3704	1.2476	-0.1228	0.3160
	Abnormal Returns	3.4950	3.5084	0.0133	0.9690	2.2680	2.4502	0.1821	0.4626
Extreme Values	Frequency [*Return* > *M+(2)(SD)*]	0.0270	0.0290	0.0020	0.0370	0.0282	0.0300	0.0018	0.0001
	Frequency [*Return* < *M-(2)(SD)*]	0.0271	0.0265	-0.0007	0.4399	0.0280	0.0225	-0.0057	0.1681

Charoenrook and Daouk (2005) and Saffi and Sigurdsson (2011). Likewise, a decrease in positive skewness is consistent with the evidence of Chang *et al.* (2007) and Xu (2007). Kurtosis shows a marginal decline only in a security's raw returns. The greater frequency of extreme positive returns is inconsistent with our Hypothesis 4. However, this result suggests that relaxing short sale restrictions does not increase the possibility of frequent extreme negative returns.

5.2.2 Multivariate Analysis

In this section, we examine the distributional characteristics of stock returns following the change in regulations after controlling for other variables. Our dependent variable is the skeweness of returns, and the explanatory variables are *SS_Ratio*, *MT_Ratio*, cross-list dummy, size, turnover, and percentage of zero-return days. We test Hypothesis 2 by examining the skewness of securities' raw and abnormal returns. Table 6 reports the results.

Table 6 Cross-Sectional Regressions of Skewness

The dependent variable is the skewness of stock returns. The skewness of raw returns is calculated for each stock in the seven-month post-period. The skewness of abnormal returns is the skewness of the residuals of a regression of stock returns on the market index returns (i.e. market model) for each firm in the seven-month period following the change in regulations. *SS_Ratio* is the average of daily short sales volume divided by daily trading volume. *MT_Ratio* is the average of daily margin volume divided by daily trading volume. *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise. Market Cap is market capitalisation. Turnover is total volume traded to shares outstanding. The percent of zero returns is the average number of days a stock has a zero return, divided by the total number of days in the seven months with available return data. Bid-Ask is the closing spread scaled by price.

	Exp. Sign	Dependent Variable: Skewness of Individual Stock Raw Return	Dependent Variable: Skewness of Individual Stock Abnormal Return
		(I)	(II)
SS_Ratio	−	0.0071	-0.0231**
		(1.42)	(-2.44)
MT_Ratio	−/+	-0.0000	-0.0021
		(-0.02)	(-1.27)
Cross-List	−/+	-0.1043	-0.2793*
		(-1.30)	(-1.84)
Market Cap	−/+	-0.0000*	-0.0000
		(-1.89)	(-1.01)
Turnover	−/+	0.3845	-0.7057
		(0.13)	(-0.12)
Zero return days (%)	−/+	-0.1525	-0.4415
		(-0.32)	(-0.49)
Bid-Ask	−/+	28.7140	66.3827
		(0.91)	(1.12)
Obs.		284	284
Adj. R-Squared		0.0287	0.0208

We find evidence that short sales are associated with the decline in the skewness of abnormal returns (column II) at the 5% level. This finding is consistent with our Hypothesis 2 and the theoretical model of Xu (2007), which propose that relaxation of short sale constraints reduces skewness. Our finding is also consistent with the empirical evidence of Saffi and Sigurdsson (2011). In addition, consistent with our univaraite results, we find no relation between the skewness of securities' raw returns and short selling and/or margin trading (column I).

Table 7 Cross-Sectional Regressions of Kurtosis

The dependent variable is the kurtosis of stock returns. The kurtosis of abnormal returns is based on the residuals of a local market model regression for each firm in the seven-month period following the change in regulations. *SS_Ratio* is the average of daily short sales volume divided by daily trading volume. *MT_Ratio* is the average of daily margin volume divided by daily trading volume. *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise. Market Cap is market capitalisation. Turnover is total volume traded to shares outstanding. The percent of zero returns is the average number of days a stock has a zero return, divided by the total number of days in the seven months with available return data. Bid-Ask is the closing spread scaled by price.

	Exp. Sign	Dependent Variable: Kurtosis of Individual Stock Raw Return	Dependent Variable: Kurtosis of Individual Stock Abnormal Return
		(I)	(II)
SS_Ratio	−	-0.0745*	-0.0140
		(-1.89)	(-1.12)
MT_Ratio	−/+	0.0071	-0.0009
		(1.02)	(-0.41)
Cross-List	−	-0.4069	-0.0921
		(-0.64)	(-0.46)
Market Cap.	−	-0.0000	-0.0000
		(-0.88)	(-1.24)
Turnover	−	-30.1436	-0.8608
		(-1.26)	(-0.11)
Zero return days (%)	−/+	12.4752***	9.1847***
		(3.32)	(7.67)
Bid-Ask	−/+	266.9471	93.2130
		(1.08)	(1.18)
Obs.		284	284
Adj. R-Squared		0.0579	0.1817

Next, we test Hypothesis 3 by using the kurtosis estimated from stock returns and residuals from a market model regression (i.e. abnormal returns) as dependent variables following the relaxation of short selling and margin trading constraints. In columns I and II of Table 7, we provide the cross-sectional regression results. We find that higher short selling volume is marginally associated with lower kurtosis of raw returns at the 10% level. The kurtosis from abnormal returns is not associated with short selling or margin buying volume. In addition, we find that kurtosis increases significantly with a higher frequency of zero-return days, which is consistent with prior empirical literature. Overall, our findings are weakly consistent with Hypothesis 3 but consistent with Saffi and Sigurdsson's (2011) evidence that a relaxation in short sale constraints reduces the kurtosis of returns. Again, our regression analysis results are consistent with those of the univariate analysis, where we find a marginal decline in the kurtosis of affected securities' raw returns.

Table 8 Cross-Sectional Regressions of Extreme Returns

The dependent variable is the fraction of returns with two standard deviations below or above the seven-month post-period average. *SS_Ratio* is the average of daily short sales volume divided by daily trading volume. *MT_Ratio* is the average of daily margin volume divided by daily trading volume. *Cross-List* equals 1 if the stock is dual-listed and 0 otherwise. Market Cap is market capitalisation. Turnover is total volume traded to shares outstanding. The percent of zero returns is the average number of days a stock has a zero return, divided by the number of days in the seven months with available return data. Bid-Ask is the closing spread scaled by price.

	Exp. Sign	Dependent Variable: Frequency of Extreme Negative Stock Returns	Dependent Variable: Frequency of Extreme Positive Stock Returns
		(I)	(II)
SS_Ratio	−	-0.0001	0.0003**
		(-0.83)	(2.09)
MT_Ratio	−/+	0.0000	0.0000*
		(0.29)	(1.84)
Cross-List	−/+	0.0005	0.0001
		(0.27)	(0.03)
Market Cap	−/+	0.0000	-0.0000
		(0.86)	(-0.48)
Turnover	+	0.1229*	0.1906**
		(1.63)	(2.54)
Bid-Ask	+	-0.89175	-0.8220
		(-1.14)	(-1.06)
Zero Return days (%)	−	0.0118	0.0272**
		(0.99)	(2.31)
Obs.		284	284
Adj. R-Squared		0.0052	0.0547

Finally, we test Hypothesis 4 by estimating the relationship between short sales and margin borrowing volume and extreme returns. The results are reported in columns I and II of Table 8. For the extreme negative returns, we do not find any explanatory power for short sales and margin trading volume. However, extreme positive returns are postively associated with higher short sales and margin trading at the 5% and 10% levels, respectively. These results are inconsistent with our Hypothesis 4 but indicate that the lifting of the ban on short selling is not associated with market crashes and that the effect of margin buying dominates the effect of short selling. Further, the analysis of other controls presents a mixed picture;

affected securities with a higher turnover and a greater proportion of zero return days (i.e. lower liquidity) increase the occurence of extreme positive returns. The increase in the frequency of extreme positive raw returns is consistent with our earlier univariate results. Next, we test the changes in price clustering when price discovery is likely to improve following the lifting of short sale restrictions.

5.3 Price Clustering

We test the clustering effect of the final digits of daily closing, opening, high and low prices. Following Brown and Mitchell (2008), in the presence of cultural effects in the Chinese market where 8 (4) is considered a lucky (unlucky) number, A-share prices are likely to reveal (i) lower occurences of 2 relative to 8, (ii) lower occurences of 4 relative to 6, and (iii) lower occurences of 4 relative to 8. Therefore, we want to test whether the intensity of Chinese cultural influence on price clustering is reduced following the relaxation of short selling and margin borrowing constraints. The results of the relative frequencies are mentioned in Table 9. Firstly, consistent with prior literature, we find higher relative frequencies for numbers ending in 0 and 5 for both the pre- and post-periods. Secondly, the relative frequency of the digit 0 has significantly declined following the regulatory change and is consistent across all the daily price types. Thirdly, the variation in price clustering has substantially reduced across all price types (i.e. the standard deviation in the post-period is reduced in closing prices by 16.03%, in opening prices by 17.26%, in high prices by 27.77%, and in low prices by 23.69%). The above findings are consistent with Ball *et al.*'s (1985) evidence that price clustering is a function of uncertainity about the asset's value. If the value is not well-known, prices are more likely to cluster, and if the value is well-known, clustering is likely to decline.

Fourthly, the relative frequency of the digit 4 has increased for all the daily price types following the removal of short selling and margin buying restrictions. However, the increase in the relative frequency of end digit 4 is significant in the daily closing and low prices. On the other hand, the relative frequency of prices ending in the digit 8 provides a mixed picture (i.e. there is no change in the daily closing and high prices but a significant increase in the daily opening and low prices). Overall, the results suggest that avoidance of prices ending in 4, which is considered to be an undesirable number, is reduced following the inception of margin trading and short selling, whereas the digit 8 is still favoured by Chinese investors. Thus it seems that the introduction of short selling activities has somewhat weakened the influence of cultural effects in the Chinese market, consistent with the study of Aitken *et al.* (1996) on the Australian stock market.

Table 10 indicates the average of daily ratios in the pre- and post-periods for 2 *vs.* 8, 4 *vs.* 6, and 4 *vs.* 8. The results reveal that the ratio of closing prices ending with the digit 4 to those ending with the digit 8 increases significantly in the post-period. Further, the proportion of 4 *vs.* 8 daily ratios of less than one significantly declines from 63% in the

Table 9 Relative Frequencies of Clustering Digit for Daily Closing, Opening, High, and Low Prices

This table provides the relative frequencies (in percentage) with which prices with the relevant end digits (0-9) are observed for affected securities seven months before and after the regulatory change in short sales and margin trading. Clustering behaviour is examined for closing, opening, high, and low prices for each day. The p-value of differences between the post- and pre-periods is also reported. All prices are clustered at the second decimal place.

	Closing			Opening			High			Low		
Digit	Pre	Post	p-value	Pre	Post	p-value	Pre	Post	p-value	Pre	Post	p-value
0	14.49	13.85	0.0109	21.72	19.72	0.0001	17.60	15.45	0.0001	21.23	18.59	0.0001
1	9.07	9.51	0.0336	8.53	8.54	0.9767	6.26	7.13	0.0001	10.19	10.27	0.7050
2	9.36	9.25	0.5952	8.18	8.47	0.1496	8.29	8.72	0.0001	8.91	9.24	0.1021
3	9.16	9.13	0.8617	8.02	8.32	0.1247	8.38	8.67	0.1548	8.66	8.80	0.5104
4	8.81	9.31	0.0141	7.01	7.28	0.1455	8.65	8.81	0.4248	6.46	7.21	0.0001
5	9.98	10.45	0.0318	12.72	12.41	0.1884	12.78	12.75	0.8807	11.54	11.72	0.4170
6	9.21	9.28	0.7540	7.73	8.39	0.0007	8.06	8.98	0.0001	8.20	8.69	0.0139
7	8.74	8.78	0.8622	7.81	7.93	0.5126	9.18	9.29	0.5769	7.71	7.95	0.1995
8	10.41	10.23	0.4118	9.71	10.39	0.0016	10.85	10.77	0.7035	9.69	10.10	0.0567
9	10.68	10.19	0.0270	8.50	8.53	0.9001	9.85	9.41	0.0378	7.36	7.39	0.8753
0-9	100.00	100.00		100.00	100.00		100.00	100.00		100.00	100.00	
	Pre	Post	% Diff.	Pre	Post	% Diff.	Pre	Post	% Diff.	Pre	Post	% Diff.
Std. Dev.	1.71	1.46	-16.03	4.41	3.71	-17.26	3.19	2.42	-27.77	4.21	3.32	-23.69
Ratios:	Pre	Post	p-value	Pre	Post	p-value	Pre	Post	p-value	Pre	Post	p-value
4 *v* 6	0.96	1.00	0.0000	0.91	0.87	0.0000	1.07	0.98	0.0000	0.79	0.83	0.0000
2 *v* 8	0.90	0.90	0.4585	0.84	0.82	0.0011	0.76	0.81	0.0000	0.92	0.91	0.5482
4 *v* 8	0.85	0.91	0.0000	0.72	0.70	0.0362	0.80	0.82	0.0134	0.67	0.71	0.0000

pre-period to 56% in the post-period at the 10% level, suggesting an increase in the frequency of the unlucky final digit 4, compared to the lucky 8, in closing prices following the lifting of short sale constraints. However, the comparisons of the daily ratios of end numbers 2 *vs.* 8 and 4 *vs.* 6 show no significant change in the post-period. Thus, the evidence is consistent with the argument made by Aitken *et al.* (1996).

Table 10 Univariate Analysis for the Distribution of the Daily Ratios

This table provides summary statistics and the difference in the means and medians, using the *t*-test and Wilcoxon rank sum test, of the distribution of daily ratios for all affected securities. The ratios are based on daily closing prices. The ratios presented are 2 *vs.* 8, 4 *vs.* 6, and 4 *vs.* 8. These daily ratios are calculated by determining the number of observations each day with data available for each of the respective digits. The summary statistics are then the aggregate ratios computed across all the days for the pre- and post-periods of the entire sample. For the 2 *vs.* 8 comparisons, the expectation is that the frequency of the occurrence of 2 would increase relative to that of 8 in the post-period. For the 4 *vs.* 6 comparisons, the expectation is that the frequency of the occurrence of 4 would increase relative to that of 6 in the post-period. Similarly, for the 4 *vs.* 8 comparisons, the expectation is that the frequency of occurrence of 4 would increase relative to that of 8 in the post-period. Thus, we expect mean and median ratios to increase following the inception of short sales and margin trading in the post-period. The p-value of differences is also reported. All prices are clustered at the second decimal place.

	2 *vs.* 8			4 *vs.* 6			4 *vs.* 8		
	Pre	Post	Diff. p-value	Pre	Post	Diff. p-value	Pre	Post	Diff. p-value
Predicted ratio (#1/#2)									
Average daily ratio	1.01	1.05	0.4039	1.06	1.14	0.1181	0.94	1.04	0.0515
Median daily ratio	0.90	0.90	0.6794	0.95	1.00	0.4061	0.86	0.90	0.0727
Proportion of daily ratios <1	0.58	0.56	0.6532	0.51	0.49	0.5485	0.63	0.56	0.0837

VI. Conclusion

The CSRC allowed short sales and margin buying initially for 90 A-shares on 31 March 2010 as a pilot programme and subsequently converted this into regular business by increasing the number of securities to 197 on 5 December 2011. Both regulatory events happened at a critical time: that is, the pilot programme and subsequent conversion to regular business were initiated when financial regulators around the world were devising new rules to restrain short selling activities to deal with the aftershocks of the GFC and the euro debt crisis. We investigate the impact of the removal of short sale and margin trading restrictions on information efficiency measures, the distributional characteristics of stock returns, and price clustering.

On average, we find that there is no consistent change in pricing efficiency across the various measures we employ following the commencement of short sales and margin trading in China. The first measure of efficiency (R-Squared) shows mixed findings in the post-period, suggesting a slight improvement in information efficiency following the removal of the short sales ban. The second measure of efficiency (cross-autocorrelation) declines significantly in the post-period, suggesting the faster incorporation of information into prices following the regulatory change. In addition, the two price delay measures (*D1* and *D2*) show no changes following the relaxation of short selling and margin borrowing constraints. Thus, the evidence is somewhat contradictory to the prior literature, which suggests that security prices adjust faster in such environments where short sale constraints are minimal. Nevertheless, the mixed evidence could be a result of the simultaneous launch of both short sales and margin buys for selected securities. Moreover, we perform certain robustness tests on weekly return data, but again the evidence is mixed.

The abnormal returns of the affected securities experience a statistically significant decline in positive skewness following the inception of short selling activities. This is consistent with the theoretical model of Xu (2007) and the empirical findings of Chang *et al.* (2007), suggesting that the greater divergence of investors' views along with short sale restrictions increase the skewness of stock returns. Moreover, we find no change in the kurtosis of abnormal returns and a significant increase in the occurrence of extreme positive returns for affected securities with higher short selling and margin trading. The higher frequency of extreme positive returns for securities with greater short selling activities suggests that the removal of short sale constraints is not linked with extreme negative returns in the Chinese market.

Finally, we investigate the relationship between price clustering and the removal of short selling and margin trading restrictions. In Chinese culture, any numbers ending in the digit 8 are considered attractive and lucky, while numbers ending in 4 are considered unfavourable and unlucky. The previous literature finds a prevalence of price clustering in the final digits due to the influence of non-fundamental trading and superstitious beliefs. We find a significant increase in the relative frequency of daily closing prices ending with the digit 4 following the change in regulations. Similarly, this increasing trend is also observed in daily low prices. Further, the daily average proportion of 4 *vs.* 8 ratios, which is less than one, significantly declines in the post-period. However, the relative frequency of the number 8 in different daily prices shows mixed evidence. Overall, these results provide some support for the hypothesis that cultural influences are less pronounced following the regulatory change.

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Appendix Univariate Analysis – Changes in Information Efficiency – Affected and Non-affected Subsamples

This table reports the cross-sectional average of the estimated measures of information efficiency. The columns labelled 'Pre' show the cross-sectional mean and median of each measure for the one-year weekly data before the inception of short selling and margin trading. The columns labelled 'Post' show the average of variables during the one-year weekly data following the introduction. A minimum of at least 40 weekly observations are required for each stock in both the pre- and post-periods. The paired t-test and the Wilcoxon rank non-parametric test are used to analyse the difference between the two periods. Also reported are the 'Diff' of Post minus Pre and associated p-values.

Affected minus Unaffected (N=90)	Mean				Median			
	Pre	Post	Diff	*p*-value	Pre	Post	Diff	*p*-value
R-Squared	0.0445	0.0140	-0.0305	0.0747	0.0179	-0.0199	-0.0377	0.1221
Cross Auto-correlation	-0.0282	-0.0092	0.0189	0.1528	-0.0271	-0.0229	0.0041	0.1518
D1	0.0591	0.0139	-0.0452	0.0393	0.0056	-0.0076	-0.0132	0.0681