Noise Trading, Underreaction, Overreaction and Information Pricing Error Contaminate the Chinese Stock Market

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Abstract

We test for noise trader risk in China stock market through the interaction between noise traders and information traders by applying the Information-Adjusted Noise Model. Information traders tend to underreact, overreact or increase information pricing error (IPE effects) on the stock market. Consequently information traders in China drive price away from fundamental level rather than correcting for the price error. We test our model using data from the Shenzhen Stock Exchange. We finally present evidence that the market is informational inefficient. The most common violation of information efficiency is overreaction and information pricing error.

Keywords: Noise traders, Information Traders, Information Efficiency, Underreaction, Overreaction, IPE

1. Introduction

Efficient market hypothesis (EMH) argues that noise traders are marginal traders who disappear as a result of arbitrage trading activities. Black (1986) questions this paradigm and recognizes the importance of noise traders as it contributes to the liquidity of a market. Subsequent study such as De Long, Shleifer, Summers, and Waldman (1990) [DSSW (1990) thereafter] provided direct empirical evidence against this section of the EMH by showing that this type of traders influences the market through noise trader risk. The research interest in the area kept growing when the problem of identification of a noise trader was later simplified by Shefrin and Statman (1994) who classified any trader not trading on information as noise traders. This led to the development of a number of models like Sias, Starks and Tinic (2001), Osler (1998) and Ramiah and Davidson (2007) that attempt to quantity noise traders. Whilst the earlier segment of the literature focused on the development of models to capture noise traders, current research is undertaken to test the validity of these existing models. In this study, we test for the existence of noise traders as another form of market inefficiency.

One of the underlying assumptions of most asset pricing models is homogeneity among traders in a perfect capital market scenario and this assumption was later relaxed by Shefrin and Statman (1994); leading to the behavioural asset pricing model (BAPM). They postulate that there are two types of traders namely noise traders and information traders which cause heterogeneity amongst traders. Furthermore in the behavioural finance literature, we detected four subcategories of noise traders namely small retail investors (or mums and dads), wealthy individuals, smart money and sophisticated traders. The introduction of sophisticated users in the model changes the dynamics of the market in that the proportion of noise traders increases significantly and the consequences cannot be negligible. There is enough evidence to demonstrate that professionals-sophisticated users can commit mistakes through underreaction, overreaction and may even turn into noise traders themselves. Ramiah and Davidson (2007) refers to the third mistake as information pricing error (IPE) and provide evidence of this issue and underreaction in the Australian equity market. DDSW (1990) is another classic paper that validates the presence of noise traders through noise trader risk which in turn divergence market prices away from the fundamental values.

There is a new wave of study that discusses the various disturbances in asset prices in China. For instance, Chen, Rui and Wang (2005) shows that Chinese investors have a tendency to overreact to good (bad) news and underreact to bad (good) news in a bullish (bearish) market. Lee and Rui (2000) concludes their paper by arguing that foreign investors may lack the knowledge of the Chinese market and when we consider other research papers in this area, it leads us to believe that asset prices in China may not be trading at their desired fundamental values. Our research explores whether these divergence in asset prices (if any) can be explained by the noise trading theory. Given the recent evidence on the irrational behaviour within the Chinese market, China provides an ideal testing ground for our hypothesis and we focus on the Shenzhen Stock Exchange (SZSE). Using the information adjusted noise model (IAMN) developed Ramiah and Davidson (2007) we test whether there is noise trader risk, overreaction, underreaction and IPE on the Shenzhen A share market. This study also determines whether noise trader risk is priced. Hence our contribution is of two folds. It is the first study that simultaneously tests for noise trader risk, overreaction, underreaction and IPE in that market and explains the relationship between noise trader risk and return in China. Our findings do not support the EMH in that we observed a strong presence of noise traders in China. Our results show that the Chinese market trade at irrational values in most of the cases that we study. We provide evidence of overreaction, underreaction and IPE in the Shenzhen market and that opportunities to profit from noise traders exist. In the second section we describe our data and methodology, the third section contains our empirical estimates and fourth section outlines our conclusion.

2. Data and Methodology

Data

The daily stock return for all listed firms, volume traded, number of shares outstanding, price, risk free rate and market return used in this study were obtained from DataStream. Firms that did not have enough information to conduct our tests were removed from the sample. The daily data covers the period January 1st, 2002 to August 24th, 2010 and our final sample consists of 180 firms listed on the A shares of the Shenzhen Stock Exchange (SZSE). Information arrival is captured through the announcements made on the SZSE and we hand collected this data from the SZSE website. This manual collection is a long and expensive exercise and the number of news arrival for these 180 firms over the period of our study is 28,106.

Methodology

The methodology of Ramiah and Davidson (2007) is followed closely in this experiment. In an effort to capture the noise trader risk, we start by estimating the CAPM using the formula below

$$\tilde{r}_{it} - \tilde{r}_{ft} = \phi_i + \beta_i^C[\tilde{r}_{mt} - \tilde{r}_{ft}] + \tilde{\varepsilon}_{it} \qquad (1)$$

where $\tilde{r}_{it}$ is the asset i's return at time t, $\tilde{r}_{ft}$ is the risk free rate of return, $\tilde{r}_{mt}$ is the daily return on the Shenzhen Composite Market Index, epsilon($\tilde{\varepsilon}_{it}$) is the error term, phi(ϕ_i) is the interception equation ($E(\emptyset_i) = 0$) and β_i^C is the CAPM beta.

The second step is to estimate the behavioural asset pricing model (BAPM) and equation 2 below illustrate this model

$$\tilde{r}_{it} - \tilde{r}_{ft} = \omega_i + \beta_i^B\left[\breve{\tilde{R}}_{mt}^B - \tilde{r}_{ft}\right] + \tilde{\varepsilon}_{it} \qquad (2)$$

where omega (ω_i) is the interception equation $(E(\omega_i) = 0)$ and β_i^B is the BAPM beta. $\breve{R}_{mt}^B$ is the return on the sentiment index at time t and the remaining variables are defined as in equation 1. The difference between the BAPM and CAPM lies in the sentiment index. Consistent with Ramiah and Davidson (2007), we followed the preferred stock hypothesis to build our sentiment index and we utilize the top ten preferred stocks on the SZSE to form this behavioural index. Such index, however, already exists in a different form in China and is known as the Dragon index.

Equations (1) and (2) are estimated on a daily basis using a window of the previous 260 days and the daily CAPM and BAPM betas are generated. On a daily basis, the difference between these two betas are estimated and this is referred to as behavioural error (BE) and is represented by

$$BE_{it} = \beta_{it}^C - \beta_{it}^B \quad (3)$$

Shefrin and Statman (1994) use this as a measure to determine whether the market is behavioural inefficient and we can regard this as a naïve proxy for noise trading activities. The variation in behavioural errors (ΔBE_{it}) can be explained by a number of factors including firm specific information, external information arrival, portfolio rebalancing, liquidity trades as well as noise trading activities. Holding external information arrival, portfolio rebalancing, liquidity trades constant, we control for firm specific information in the BE. This leads to the implicit assumption that the unexplained variation in BE is a direct result of noise trading activities and is regarded as noise trader risk. The process of extracting the information content out the BE is known as the information adjusted noise model (IAMN) and is shown in the equation 4 below.

$$\Delta BE_{it} = \alpha + \gamma IE_{it} + \varepsilon_{it} \quad (4)$$

Where IE is the firm specific information, i.e., the new information release.

Information arrival can be interpreted differently from different traders. What constitute a good new for one trader may be perceived as bad news by another trader as they can both have different prior and posterior beliefs. IE does not distinguish between good news and bad new and takes the form of a dummy variable. The dummy variable takes the value of one on information arrival day and zero otherwise. Alpha (α) is the mean change in the behavioral error attributable to noise traders and gamma (γ) is the proportion of the mean change in behavioral error attributable to information traders.

According to the efficient market hypothesis (EMH), noise traders are marginal traders who disappear as a result of arbitrage trading activities. If the EMH was to hold, then the IAMN, i.e. the change in behavioural error must be equal to zero ($\Delta \mathrm{BE}_{\mathrm{it}} = 0$). When$\Delta \mathrm{BE}_{\mathrm{it}} \neq 0$, it implies that the market is inefficient as noise traders exist in the market.

Given that a dummy variable is used in equation 4, this equation is simplified to the following equation on non-information days as the dummy variable equals to zero

$$\Delta \mathrm{BE}_{\mathrm{it}} = \alpha + \varepsilon_{\mathrm{it}} \qquad (4.1)$$

Information traders enter the market only when there is new information arrival. In the absence of news arrival, any trader in the model is a noise trader and this is shown in equation (4.1).

On information days a number of possibilities may occur. For instance noise traders may commit an error ($\alpha > 0$) and information traders (γ) can react in three different ways namely no reaction ($\gamma = 0$), oppose the noise traders ($\gamma < 0$) or even join the noise traders ($\gamma > 0$). When information traders do not react, it creates another form of inefficiency as there is still a residue of α in the market. In a scenario where information traders oppose noise traders, the market will be efficient if and only if the magnitude of error α is equal to the magnitude of γ, i.e. $(|\alpha| = |\gamma|)$ as there will be no residue left. Where the information traders fails to clear the entire error α, a residue will remain into the system. In the event that the information traders joint the noise traders, the residue α will be increased by γ. The residue discussed under these different scenarios, the residue is our measure of noise trader risk (μ) and can be written as

$$\mu = \alpha + \gamma \qquad (5)$$

According to the IAMN, the EMH will hold when the equation 5 equals to zero as there is no noise trader risk on the market. The existence of noise trader risk $(\mu = \alpha + \gamma \neq 0)$, implies that the market is inefficient and this gives rise to three different effects namely underreaction, overreaction and information pricing error. When a noise trader commit an error (α > 0) and the information traders oppose them but fails to ensure that the EMH holds, it shows that the information traders has underreacted to this new arrival. This situation is labeled as positive underreaction (U+) and when α < 0, and an information trader underreact, it is labeled as (U-). If the information traders were to oppose the noise traders but overshoot the magnitude of alpha, then we have an overreaction scenario. When the information traders do not oppose the noise traders but decides to join them by adding to the existing errors, this is regarded as an information pricing error (IPE). Similar to underreaction, both overreaction and IPE can be positive and negative, i.e. O (+), O (-), IPE (+) and IPE (-). For any of the above inefficient market to hold, the following sets of conditions need to prevail namely:

Condition for U (+) to occur requires α > 0, γ < 0 and μ > 0 (C1)

Condition for U (-) to occur requires α < 0, γ > 0 and μ < 0 (C2)

Condition for O (+) to occur requires α < 0, γ > 0 and μ > 0 (C3)

Condition for O (-) to occur requires α > 0, γ < 0 and μ < 0 (C4)

Condition for IPE (+) to occur requires α > 0 and γ > 0 (C5)

Condition for IPE (-) to occur requires α < 0 and γ < 0 (C6)

Davidson and Ramiah (2011) argue that identifying inefficient markets is a real challenge but the most important question is whether arbitrageurs can profit from these inefficiencies. We thus follow their methodology to test if noise trading strategy is profitable in China and this can be regarded as a direct test of the practical potentials of the IAMN. So far, we have discussed two measures of noise trading activities namely behavioural error as a naïve form of noise trading activities and mu as a more accurate measure of noise trader risk. By linking any of these two measures with an asset return, we will be able to determine whether noise trading is a rewarding exercise. The following model is estimated for that purpose.

$$\tilde{r}_{it} = \lambda_{1,i} + \lambda_{2,i} \Delta\mu_{t-1} + \tilde{\varepsilon}_{it} \qquad (6)$$

In equation 6, the dependent variable is the return of an equity asset listed on the SZSE and the independent variable is the lagged value of change in noise trader risk($\Delta\mu_{t-1}$).The lagged value of changed in mu is used, because it assumes that the trader identifies noise traders in one period and then opposes them in the subsequent period. λ_1 and λ_2 are the intercept and slope of the model respectively. λ_2 captures the relationship between noise trading and return and can take three values namely $\lambda_2 = 0$, $\lambda_2 > 0$, or $\lambda_2 < 0$. In the first case, it implies that noise traders do not affect the return of assets. The second possibility, $\lambda_2 > 0$, shows a positive relationship between stock returns and the change in mu and is known as a systematic noise effect (SNE). Such occurrence indicates that noise traders add systematic risk to the market and supports DSSW (1990) in that noise traders earn more than information traders by increasing their risk exposure. The last outcome, $\lambda_2 < 0$, depicts a negative relationship between stock returns and changes in noise trader risk and is known as the cash noise effect (CNE). This would suggest that information traders could earn profits by undertaking contrarian investment strategies relative to the noise traders. Similar to equation 6, we can develop another test using the naïve proxy for noise trader risk namely behavioural error giving rise to the following equation 7.

$$\tilde{r}_{it} = \pi_{1,i} + \pi_{2,i}\Delta BE_{t-1} + \tilde{\varepsilon}_{it} \tag{7}$$

Standard residual diagnostics tests like normality, autocorrelation and auto regressive conditional heteroscedasticity (ARCH) are conducted on all the regression models. Problems like autocorrelations were corrected by including the appropriate autoregressive and moving average terms and a generalised auto regressive conditional heteroscedasticity, GARCH (1,1), was applied to correct for the ARCH effects. Another issue worth pointing out in this study is the rollover technique used to estimate the daily betas (both CAPM and BAPM) generates highly correlated and dependent betas, and thus affects the statistical significance. Similar to Ramiah and Davidson (2007), the standard errors of the betas were adjusted to correct for the dependence.

The sentiment index in China is not readily available and was constructed. It consists of the top ten popular stocks on the SZSE A share and similar to the market, we refer to that index as Dragon index. The Dragon index was then calculated as per equation 8.

$$DragonIndex_t = \frac{\sum_{i=1}^{10} \left(S_i * P_{it}\right)}{\sum_{i=1}^{10} \left(S_{i0} * P_{i0}\right)} * I_o \tag{8}$$

Where S_i is the number of shares outstanding in stock *i*, S_{i0} is the number of shares outstanding at time t=0, P_{i0} is the price of stock *i* at time t=0, and I_0 is an arbitrary multiplier. The arbitrary is a fixed value that allows us to get a value close to the Shenzhen Composite Market Index for comparison and graphical illustrations.

3.0 Empirical Results

This section reports the results of noise trader risk, underreaction, overreaction, IPE, EMH, systematic noise effect and cash noise effect on the Shenzhen Stock Exchange. Using the CAPM, BAPM and the IANM, we test whether the Chinese market is inefficient in terms of noise trading activities. We also test if arbitrageurs can profit from noise traders. We confirm that there is a strong presence of noise traders in the Chinese market as there is evidence of underreaction, overreaction and IPE. Surprisingly, there is little evidence in favour of the EMH when it comes to noise traders in China. Interestingly, we find that there is a relationship between past noise trader risk and the return of an asset.

Table 1 shows the descriptive statistics for the two indices, Shenzhen Composite Market Index (SCMI) and Dragon index, used in the estimation of the CAPM and BAPM respectively. In the second column of Table 1, we can observe the performance of these two indices in terms of return and risk for the entire period 2002-2010. The mean return of the Dragon index and the SCMI is 0.6881% and 0.0385% respectively. Such difference[1] is quite large and is consistent across all the remaining sub periods. It implies that the behavioural index formed on the preferred stock hypothesis, in particular the Dragon index consistently outperform the SCMI. The variance[2] of the Dragon index is also consistently higher than the SCMI and this occurs because there is a relatively lower amount of stocks within the sentiment index. Although there is a high correlation between, we can still observe different outcomes from these indices. The next step will be to determine whether there is a difference between the behavioural beta and the CAPM beta.

Evidence of Irrationality

As discussed earlier it is possible to discern the movement of noise traders using the naïve approach of behavioural errors. Table 2 shows the average CAPM beta, average

[1] This difference is statistically different from zero as the t-statistics is 21.97
[2] There is a statistical difference as the p-value of the F-Statistics is less than 0.05.

BAPM beta and average behavioural error for 180 Chinese firms for the period 2002-2010. From the second column of Table 2, we observe that average CAPM beta is 1.022, BAPM beta is 0.5688, average BE is 0.4532 and that these average are statistically significant. Consistent with Ramiah and Davidson (2007), we find that CAPM beta is consistently higher than the behavioural beta and that distortion through BE exists in the Chinese equity market. The sub periods analysis reinforces this view and Figure 1 shows further illustrate this point.

The second step in the process of calculating noise trader risk is to extract the information content out the observed behavioural error. Tables 3, 4 and 5 report the average alpha, average gamma and average mu for the periods of our study respectively. Alpha captures the noise element of non-information information traders and the average alpha for the period 2002-2010 is statistically insignificant. However, when our overall sample is broken up into individual years (see Table 3), we find a strong statistical significance for alpha (except for 2008). We detect a cyclical behaviour whereby alpha is positive in one period, becomes negative in the subsequent period and then back to positive. For the overall sample, average gamma is negative and when the sample is disaggregated in years, we find that gamma was positive in 2002 and decreases systematically over the following years (see Table 4). Gamma captures the behaviour of information traders. When alpha and gamma is combined, mu is generated and this represents the measure of noise trader risk in China. The results in Table 5 shows a strong presence of noise traders within the Shenzhen equity market as mu is statistically significant for all periods studied (except for 2004). The existence of mu is an indication that the Chinese equity market trades at irrational levels as noise traders distort the equity prices.

By studying the interaction between information traders and noise traders through the IAMN that is by combining alpha, beta and mu we are able to assess whether there is overreaction, underreaction or IPE on the Chinese market. Table 6 shows the different irrational behaviour that we observe through the IAMN in the Shenzhen market. Over the period 2002-2010, we study 28106 news arrivals on the Shenzhen A share market. We find that the EMH in terms of absence of noise traders occurs in only seven instances and that the EMH does not hold in 99.98% of the times. This is direct evidence that noise traders do exist in China Shenzhen A share market. Such percentage is relatively high given that Ramiah and Davidson (2007) observed that the Australian market was inefficient around 63% of the times.

It is possible to decompose the noise trading activity into overreaction, underreaction and IPE. We observe from Table 6 that percentage of IPE, overreaction and underreaction is 40.71%, 40.55% and 18.72% respectively. The two major problems in the Shenzhen market are IPE and overreaction and Ramiah and Davidson (2007) shows that the Australian equity market is contaminated with underreaction and IPE. IPE is the scenario where information traders becomes noise traders and can be regarded as a more serious problem as it shows that sophisticated users like professional traders make mistakes by turning into noise traders. Overreaction implies that Chinese traders are opposing noise traders but they overshoot their forecasting error. This is a less severe case in the sense that proper actions are undertaken to eliminate noise traders but they happen to get the magnitude wrong. This can be explained through the lack of quantitative models to quantify noise trader risk. Underreaction is not of negligible proportion within that market and can also be explained by the lack of tools to predict the presence of noise traders.

Another advantage of the IAMN is that it can identify the variations that may occur within these three different effects. All of these effects can be split onto positive and negative. For instance, IPE can be segregated into IPE (+) and IPE (-) and the percentage of occurrence is around 15% and 25% respectively. Overreaction can be divided into overreaction (+) and overreaction (-) and the proportion is around 17% and 23% respectively. Underreaction (+) and (-) are of equal proportion. The implication is that traders must be careful in their actions against noise traders as different strategy may be required for the one particular effect. The sub periods analysis of Table 6 reinforces our view that three irrational behaviours occur on the Chinese market and it provides additional knowledge as to how these effects varies over time. For instance, it shows that underreaction was around 25% at the start of our sample (2002), decreases to 10% in 2008 and then increases to around 38% in 2010. IPE, on the other hand, is consistent around the 40% throughout the sub samples and then drastically dropped to around 12%. Overreaction reaches up to 52% in 2008 and may be attributed to the global financial crisis.

Now that we have established a link between noise trading activities in terms of noise trader risk, IPE, overreaction and underreaction and the Chinese equity market, the next step is to test if an arbitrageur can profit from the IAMN. It is therefore important to estimate equation 6 to determine whether first noise trader risk is priced (that is showing a relationship between asset returns and noise trader risk) and secondly to validate either the systematic noise effect (SNE) or the cash noise effect (CNE). Equation 6 is estimated for all 180 Chinese firms and we count the number of firms where the slope of equation 6 is statistically significant. Table 7 shows that almost 25% (that is 44 firms) of the firms studied displayed a relationship between noise trader risk (mu) and the return of the firm. We consider this as evidence that noise trader risk is priced in the Chinese market. When these 44 firms are subcategorized into SNE and CNE, we find around 10% of our sample of firms (19 firms) shows evidence of SNE and 25 firms displayed CNE (18.89% as shown in Table 7). Equation 7 is also estimated for that purpose but we could not establish an adequate link between BE and return of the equity assets as only two companies displayed a positive relationship between BE and returns (see Table 7 that shows a negligible percentage of 1.11%).

Conclusion

The first conclusion drawn from this study is that IANM can be applied in China and provides a measure of noise trader risk. The major problem of this model lies in the collection of the news arrival variable which is a labour intensive, time consuming and expensive exercise. The benefits of this paper, however, are that it provides a quantitative explanation to the overreaction and underreaction phenomenon in that market. Further, this paper enables one to observe the behaviour information traders towards noise traders and in particular circumstances where the information traders commit mistakes. Our study shows that there is evidence of noise trader risk, IPE, underreaction and overreaction in China. Such evidence challenges the notion of the EMH. The major problems in China are a high presence of noise traders, IPE and overreaction. Interestingly, we show a relationship between noise trader risk and the return of the equity asset.

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Table 1. Descriptive Statistics of the Returns on the Shenzhen Composite Market Index and Returns on the Dragon Index

	2002-2010	2010	2009	2008	2007	2006	2005	2004	2003	2002
Dragon Index										
Mean	0.006881	0.008013	0.010402	0.000217	0.015108	0.011909	0.002214	0.003155	0.006442	0.004917
Median	0.005843	0.006012	0.012305	0.000000	0.015466	0.012582	0.002160	0.000135	0.004996	0.002390
Stdev	0.027367	0.044267	0.026188	0.034717	0.033181	0.023966	0.020673	0.019320	0.017387	0.019351
Variance	0.000749	0.001960	0.000686	0.001205	0.001101	0.000574	0.000427	0.000373	0.000302	0.000374
Obs	2256	168	261	262	261	260	260	262	261	261
Shenzhen Composite Market Index										
Mean	0.000385	-0.000335	0.002970	-0.003669	0.003702	0.002618	-0.000480	-0.000692	-0.000101	-0.000775
Median	0.000269	0.001101	0.005005	-0.001234	0.005936	0.003084	0.000000	0.000000	0.000000	0.000000
Stdev	0.018456	0.016250	0.020484	0.029376	0.022625	0.013590	0.014518	0.013365	0.010377	0.016212
Variance	0.000341	0.000264	0.000420	0.000863	0.000512	0.000185	0.000211	0.000179	0.000108	0.000263
Obs	2256	168	261	262	261	260	260	262	261	261
Testing if the returns are different										
t-statistics	21.979710	2.711155	10.157097	3.120484	9.034831	11.680844	2.510842	4.220564	8.007550	8.696995
p-Value	0.000000	0.007406	0.000000	0.002008	0.000000	0.000000	0.012654	0.000034	0.000000	0.000000
Testing if the variance is different										
F-Statistic (p-Value)	0.000000	0.000000	0.000246	0.007145	0.000000	0.000000	0.000000	0.000000	0.000000	0.004460

Table 2. Average CAPM beta, BAPM beta and Behavioural Error (BE) for the period 2002-2010 for Chinese firms

	2002-2010	2002	2003	2004	2005	2006	2007	2008	2009	2010
CAPM Beta	1.022	1.0152	1.025	1.0275	1.0234	1.0298	1.0016	1.0243	1.0588	1.0108
T-Stats for CAPM beta = 0	60.56	40.46	53.82	57.07	22.66	69.22	44.95	60.53	58.93	39.44
T-Stats for CAPM beta = 1	14.23	26.11	98.74	68.45	50.34	22.29	2	14.27	42.17	42.52
BAPM Beta	0.5688	0.7561	0.5683	0.4909	0.5754	0.4528	0.5322	0.569	0.7644	0.349
T-Stats for BAPM beta = 0	55.38	475.6	95.21	138.96	602.79	148.15	159.05	113.05	378.19	27.96
T-Stats for BAPM beta < 1	-41.98	-53.42	-72.33	-44.12	-44.75	-17.05	-39.81	-35.62	-16.55	-52.15
Behavioural Error (BE)	0.4532	0.2591	0.4567	0.5366	0.448	0.5771	0.4694	0.4553	0.2944	0.6618
T-Stats for BE = 0	46.11	73.64	75.7	52.71	31.67	43.18	16.33	33.63	22.45	53.9
Obs	180	172	173	173	178	178	178	180	180	180

Table 3. The Descriptive Statistics for the Mean Alpha

	ALPHA									
Period	02-10	2010	2009	2008	2007	2006	2005	2004	2003	2002
Mean	0.00004	0.00156	-0.00059	0.00000	-0.00036	0.00054	-0.00032	0.00032	0.00075	-0.00106
Standard Error*	0.00006	0.00005	0.00002	0.00001	0.00003	0.00002	0.00001	0.00004	0.00002	0.00004
Median	0.00003	0.00159	-0.00062	-0.00002	-0.00023	0.00056	-0.00038	0.00030	0.00076	-0.00103
ST.Deviation	0.00079	0.00069	0.00020	0.00016	0.00041	0.00025	0.00016	0.00046	0.00030	0.00047
Kurtosis	15.07190	4.24912	27.46048	7.58249	0.34929	1.98057	1.27882	0.84450	0.70209	0.00765
Skewness	2.14029	-1.00572	3.62016	-1.11104	-0.58976	-0.73250	0.26678	0.47235	0.03520	-0.05722
Obs	180	180	180	178	178	178	173	173	172	172
T-Stats for Mean = 0	0.69723	30.41557	-38.57532	0.12031	-11.79430	28.90009	-25.92067	9.10860	33.11535	-29.80215

Note: The computation of the standard error and T-statistics were adjusted for interdependence

Table 4. The Descriptive Statistics for the Mean GAMMA

	GAMMA									
Period	02-10	2010	2009	2008	2007	2006	2005	2004	2003	2002
Mean	-0.00041	-0.00160	-0.00032	-0.00053	-0.00065	-0.00050	-0.00023	-0.00039	0.00008	0.00026
Standard Error*	0.00004	0.00005	0.00002	0.00001	0.00001	0.00002	0.00001	0.00002	0.00001	0.00001
Median	-0.00036	-0.00161	-0.00004	-0.00065	-0.00071	-0.00033	-0.00033	-0.00047	-0.00002	0.00031
ST.Deviation	0.00050	0.00071	0.00020	0.00009	0.00013	0.00027	0.00017	0.00028	0.00016	0.00018
Kurtosis	0.18792	0.60402	6.83582	0.62700	1.94493	2.69515	0.76628	1.10636	3.53571	4.71084
Skewness	-0.28754	0.28859	-2.24768	0.46584	-0.66981	-0.81355	0.24934	0.28091	0.61387	-0.65276
Obs	180	180	180	178	178	178	173	173	172	172
T-Stats for Mean = 0	-10.95955	-30.24770	-21.12687	-78.94930	-67.49611	-24.72725	-17.62243	-17.93562	6.14413	18.85694

Note: The computation of the standard error and T-statistics were adjusted for interdependence

Table 5. The Descriptive Statistics for the Mean MU

	MU									
Period	02-10	2010	2009	2008	2007	2006	2005	2004	2003	2002
Mean	-0.00037	-0.00004	-0.00091	-0.00053	-0.00101	0.00004	-0.00055	-0.00007	0.00083	-0.00080
Standard Error*	0.00005	0.00001	0.00003	0.00002	0.00003	0.00001	0.00002	0.00005	0.00003	0.00004
Median	-0.00032	-0.00005	-0.00061	-0.00055	-0.00105	0.00015	-0.00067	-0.00029	0.00069	-0.00064
ST.Deviation	0.00068	0.00019	0.00039	0.00020	0.00041	0.00014	0.00029	0.00072	0.00041	0.00047
Kurtosis	0.43640	0.69181	7.60762	0.60590	2.42773	2.23201	1.30157	1.35148	3.54600	4.68464
Skewness	-0.29714	0.23640	-2.27026	0.36320	-0.75698	-0.82372	0.33365	0.42808	0.83804	-0.62749
Obs	180	180	180	178	178	178	173	173	172	172
T-Stats for Mean = 0	-7.17563	-2.88890	-30.81860	-35.05578	-32.89130	3.76842	-24.89267	-1.19025	26.55338	-22.21179

Note: The computation of the standard error and T-statistics were adjusted for interdependence

Table 6. Number of Overreaction, IPE and Underreaction across 180 Firms on the Information Day

	2002-2010			Percentage								
	Number	Percentage	z-test	2002	2003	2004	2005	2006	2007	2008	2009	2010
Underreaction	5262	18.72%	105.55	25.13%	19.82%	14.34%	14.06%	11.49%	11.35%	10.52%	28.49%	38.47%
U+	2505	8.91%	30.10	1.10%	19.23%	9.45%	2.48%	9.29%	2.29%	6.61%	2.11%	37.76%
U-	2757	9.81%	36.99	24.03%	0.59%	4.89%	11.58%	2.20%	9.06%	3.91%	26.37%	0.71%
IPE	11441	40.71%	274.66	43.27%	44.81%	44.82%	47.92%	42.17%	47.26%	36.73%	43.46%	12.26%
IPE+	4277	15.22%	78.60	1.32%	41.75%	25.29%	9.70%	32.98%	9.60%	12.58%	3.55%	9.93%
IPE-	7164	25.49%	157.61	41.95%	3.06%	19.53%	38.22%	9.19%	37.65%	24.14%	39.91%	2.33%
Overreaction	11396	40.55%	273.43	31.60%	35.37%	40.84%	37.94%	46.31%	41.37%	52.73%	28.01%	49.27%
O+	4746	16.89%	91.43	29.44%	5.95%	13.10%	25.20%	10.14%	20.48%	20.14%	19.65%	2.25%
O-	6650	23.66%	143.54	2.16%	29.42%	27.74%	12.74%	36.17%	20.88%	32.60%	8.35%	47.02%
Total Inefficient Days	28099	99.98%	730.57	100.00%	100.00%	100.00%	99.92%	99.97%	99.98%	99.98%	99.95%	100.00%
EMH	7	0.02%	-38.27	0.00%	0.00%	0.00%	0.08%	0.03%	0.02%	0.02%	0.05%	0.00%
INFO	28106	100.00%	730.76									

Note: (1) Z-test is testing if the proportion is greater than 5%. (2) For brevity purposes, the number and Z-test are not reported for the sub periods

Table 7: Systematic and Cash Noise Effect in China

Effect	Slope of Equation 6 Percentage	Slope of Equation 7 Percentage
Pricing of Noise Trader Risk	24.44%	1.11%
Systematic Noise Effect	10.56%	1.11%
Cash Noise Effect	13.89%	0.00%

Figure 1 Average BAPM Beta and Average CAPM Beta of 180 companies for the period 2002-2010