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Contrarian Investment Strategies –Evidence in China Stock Market 2002-2011

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Abstract

This master thesis aims to investigate the profitability of momentum and contrarian investment strategies in Chinese "A" share market listed on both the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) from 2002 to 2011. We examined 81 strategies with various horizons based on weekly stock return. Results suggest that contrarian strategies are more likely to be successful than momentum strategies. Short- and medium-term contrarian strategies yield statistically significant abnormal profit up to 2.2% per month, however, profitability decreases as holding period gets longer. Further analysis indicates that (1) time-varying market risk could be a source of contrarian profits, but not a major one; (2) Overreaction does not contribute to contrarian profits; (3) the lead-lag structure effect is mainly responsible for contrarian profits.

Keywords: contrarian strategy, China "A" shares, overreaction, lead-lag structure, decomposition model.

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1. Introduction

The profitability of trading strategies that based on past return patterns has attracted much interest in academics. Among them, contrarian strategies based on price reversals or momentum strategies based on price continuations are the most popular. Significantly successful short- and intermediate-term momentum strategies, and long-term contrarian strategies have been well documented in the stock markets of developed countries, such as the U.S. and England, dating back to the 1980s. Other researches also focus on the emerging markets, especially in Asia. In the China stock market, short-term contrarian and intermediate momentum effect was found to have distinct pattern from that of the western countries. Considering such findings were discovered nearly10 years ago, factors such as regime shifts could have already led to much variation in the patterns. In this paper, we attempt to investigate the short-, intermediate- and long-term contrarian strategies in the Chinese "A" share markets from 2002 to 2011. We also divide our sample into sub-periods to examine the effects on abnormal profits on the financial crisis and the on-going chaos since 2007. We believe our analysis will be of interest to both technical traders and academics.

The reason that we are interested in the Chinese market is that it is a special market as Hu (1999) points out, especially in government regulation and investor compositions. As shown in the SZSE Fact Book 2009, individual investors, with only rudimentary financial knowledge, are still the dominance of China stock market despite the fact that the percentage of institutional investors is increasing throughout the years. Stock trading in China is sometimes labeled the term "stir-frying stocks" as individual stocks are traded with market rumors. Kang et al. (2002) also suggest that syndicate speculators may find it much easier to manipulate the sentiment in small stocks, giving rises for the phenomenon that returns of small firms lead returns of large firms. Such behaviors could lead to short-term momentum or long-term contrarian profits. All these have significant different implications to momentum/contrarian strategies in China.

Moreover, China is among the countries awaiting investigations for its low correlation with global market. Byströma (2011) reports that China's stock market has much weaker reaction to the global news. Sharma (2011) examines the Asian economies and documented that China is the least positively related to the US market. All these have the implication that the China stock market will provide better diversification benefits for international investors than other markets, especially big sovereignty funds such as the Norwegian Government Pension Fund – Global, who, as a matter of fact, is increasing its exposure on emerging markets. Hence, the investigation of proper investment strategy in China stock market is still attractive and interesting to the global investors and researchers.

In addition, trading environment in China has gone through several profound reforms ever since 2000. The result is a gradual and more standardized improvement on related regulations. For example, stricter IPO regulations and trading rules were exercised in 2001. B shares were opened for domestic investors, which were limited only to foreign investors prior 2001. The first open-end fund was traded in 2001. Also, the index futures became tradable and short-selling was allowed for qualified institutional investors in 2010. The China stock market is getting more and more regulated, transparent and mature. As a result, abnormal profitability could display new patterns.

We implement and analyze a wide spectrum of contrarian investment strategies from 2002 to 2011, as well as its two sub-periods, by using all the "A" shares we can find on the China stock market. In sharp contrast to the findings in the US and the European markets, but similar to the evidences that Chou et al. (2007) report in the Japanese market during 1975 to 1997, we find that contrarian strategies are profitable on all the 81 strategies we examine, and the most statistically significant contrarian profits cluster around short-term and the intermediate-term, from 1 week to 20 weeks. Contrarian profits are generated up to 2.2% per month and decrease when strategy's holding period gets longer. Our findings are distinct from that from Kang et al. (2002), who report short-term contrarian and intermediate-term momentum profit in the Chinese "A" share market during 1993 to 2000. The investigation into the sub-periods shows that momentum strategies are gradually losing ground to contrarian strategies over time, and the discovery of contrarian profits are moving towards longer formation periods after the financial crisis. We also find that time-varying market risk, considering unequal risk embedded in winner portfolio and loser portfolio, is one of the sources contributing to contrarian strategy, but not a major one. Surprisingly, overreaction is exanimated not a source of the contrarian profit, and nearly all the stocks show price continuation but not price reversal. The finding of lead-lag structure effect is consistent with Kang et al. (2002) that small stocks exhibit leading pattern towards large stocks in terms of return. An empirical decomposition of the contrarian profits suggests that lead-lag effect is the sole determinant of expected contrarian profit as compared to the US market whose contrarian profits are mostly attributed to overreaction. Mainly speaking, our results indicate that 1) the Chinese "A" share market is similar to the Japanese market but distinct from the US market in terms of contrarian/momentum patterns; and 2) the market is more rational and the participants are more long-term oriented compared with 10 years ago.

The rest of this thesis is organized into five sections. Section 2 reviews previous findings by other researchers regarding contrarian strategy and the possible sources of contrarian profit. Section 3 describes the data resources and methodologies for conducting the research. Section 4 presents our profit finding of contrarian strategies in China stock market both in the overall sample and the two subsamples (dividing point: 09 August 2007). Section 5 reports the robustness tests for time-varying risk factor, overreaction and lead-lag structure effect. Section 6 investigates the sources of contrarian profits by an extended decomposition model on Lo and MacKinley (1990) developed by Chou et.al (2007). Finally, Section 7 concludes.

2. Literature Review

In accordance with the efficient market hypothesis, as refined by Eugene Fama (1970), security prices, at any time, fully reflect all available information in an efficient market. Price changes only to reflect new information. As new information is unpredictable, price changes should be unpredictable. Thus, price is following a random walk and no investment pattern can be discovered for the purpose to capture excess return. It means that no investors can outprofit the others by predicting the stock returns. Among the three versions of EMH, the weak-form hypothesis suggests that all historical prices and returns have been reflected on current prices. Thus no technical analysis can predict or help to form strategies to beat the market. However, empirical tests using serial correlation on stock returns discover that stock market returns have a tendency to be related to past stock returns, contradicting to the weak-form EMH. Considerable quantities of financial literatures, since 1980s, have shown that historical stock returns have predictability for future stock returns on different time horizons, challenging the weak-form EMH in the tested markets. For instance, Lo and Mackinlay (1988) report weak positive serial correlation on short horizon (1-6 months) that positive past return leads to positive current return when examining the US market index. For individual securities, reversal effect seems more common as indicated by Lehmann (1990) and Jagedeesh (1990), as U.S. stocks with positive past return tend to reverse and perform poorly later on. Moreover, portfolio of US stocks experiences continuation (momentum) effects on intermediate horizon (3-12 months) as documented by Jagedeesh and Titman (1993). On the other hand, Debondt and Thaler (1985, 1987) find out that in US market reversal (contrarian) effect happens on long horizon (3-5 years) that recent loser portfolios outperform recent winners.

These findings on continuation and reversal effects imply that abnormal profits can be exploited by forming momentum and contrarian strategies. A momentum (strengthen) strategy is to buy the portfolios consisting of stocks that performed well previously and to sell the portfolios consisting of stocks that performed poorly (buy past winner and sell past loser). While a contrarian strategy is to do the opposite with the belief that prior winner will become current loser. Using proceed from short-selling to invest, a zero initial investment can be constructed if the transaction cost is assumed to be zero.

Because of their arbitrage nature, momentum and contrarian strategies have been first tested and documented profitable to some extent in the U.S. market as shown above. Recently, Parhizgari and Nguyen (2008) also come up with considerable support for the presence of the momentum and contrarian strategies in the American Depositary Receipts (ADRs) market. The momentum or contrarian effects are found in non-US markets as well. Ahmet and Nusret (1999) discover long-term contrarian effects in the stock markets of seven non-US industrialized countries. Rouwenhorst (1998) reports momentum profits in 12 European equity markets. Schiereck et al. (1999) find momentum profits in the intermediate-term, and short- and long-term contrarian profits in the Germany equity market. Chang et al. (1995) reports short-term contrarian effects in the Japan stock market. Chou et al. (2007) further finds supports on contrarian profits in Japan stock market especially in very short and very long periods. There are a growing number of researches on emerging markets as well. Rouwenhorst (1999) discovers momentum profits in six out of twenty emerging equity markets. Hameed and Ting (2000) document short-term contrarian profits in the Malaysia stock market while Locke and Gupta (2009) report contrarian strategies profitable in the Indian market.

Specifically for China market (including Hong Kong), a few valuable literatures regarding the discovery of momentum or contrarian effects have captured researchers' interest. Ding et al. (2008) document momentum and contrarian profits in seven Pacific-Basin markets including China. They also report that this effect is especially pronounced in Hong Kong. Hameed and Yuanto (2000) find small momentum profits in six Asian stock markets covering China. Kang et al. (2002) document significant profits on short-term contrarian effect and intermediate-term momentum effect in China for the period 1993 to 2000. Investigating only the Shanghai stock exchange, Naughton (2008) suggests substantial profitability on momentum strategies from 1995 to 2005. On the other hand, Li et al. (2010) suggest no momentum profitability for the period 1994 to 2007 while coming up with the conclusion that the short-term contrarian strategies can capture, on average, 12% abnormal return annually. Du and Nie (2007) find evidences supporting profitable long-term (18-36 months) contrarian effect while rejecting intermediate momentum profits. We extend the investigation of the contrarian effect in China market to the period of financial crisis based on the method applied by Kang et al. (2002), as this is the first paper to systematically investigate the momentum/contrarian profits in China market.

How can momentum strategies or contrarian strategies beat the market as the empirical studies have shown? Former researchers try to excavate explanations to momentum and contrarian profits, of which two streams, behavioral irrationality and stock market efficiency, emerge to be dominant.

Among the alternative sources for the abnormal return brought along by contrarian strategies, investor's overreaction to information is the most notable one. As DeBondt and Thaler (1985) illustrate, overreaction hypothesis suggests that extreme price movement leads to an opposite-direction price movement later, which matches the magnitude of the initial price movement. The overreaction hypothesis is tested predictable on long-term contrarian profitability in the US market. It says that investors tend to overreact with bad, firm-specific news. The pessimistic attitude drags down the price. As what goes down must come up, the negative serial dependence of individual security raises the possibility for past losers to outperform past winners. Contrarian strategy is designed to exploits this profit. The hypothesis was supported by Lehmann (1988) and Delong et al. (1989). Later, Bacmann and Dubois (1998) test the French market and find out that short-term contrarian effect is also explainable by overreaction. The result was supported by Mun et al. (1999) with evidences from the French and German market.

Another possible explanation for contrarian effect is documented as "lead-lag structure" or "cross effects among the securities" by Lo and Mackinlay (1990). Their logic is as follows: Assume a market consisting with only two negatively correlated stocks A and B. If stock A obtained higher returns than stock B in the previous period, contrarian strategy (buy winner and sell loser) will benefit with no existence of market overreaction. They suggest that some stocks react more quickly than others in the US market, resulting in "return of large stock generally leads those of smaller ones". They also report that the lead-lag effect accounts for more than 50% of the abnormal contrarian return as indicated by their model. However, their suggestion is refuted by Jegadeesh and Titman (1995) who decompose the contrarian profits and find out that stock price reacts with delay to common factors while overreact to firm-specific information. They further document that the size-related lead-lag effect arises only when investor delay reactions to common factors. They conclude that overreaction to firm-specific information is the main contribution to contrarian profits.

A Third source of contrarian profits can be time-varying common factors. As highlighted in the research conducted by Conrad and Kaul (1998), cross-sectional dispersion in the mean return of individual securities (in the portfolio being examined) varying by time is the important determinant for short-term contrarian profits. In determining the long-term contrarian profits, Chan (1988) suggests that both the risk of individual stock (represented by beta) and the market risk premium change over time, which give rises to a reverting mean of expected return. What is more, the fact that prior losers become riskier implies higher expected return, from which contrarian strategies may benefit. Zarowin (1990) reports firm-size discrepancy is the main reason for long-term contrarian profits. It is documented that prior loser can outperform winner because of its smaller size but not of overreaction. Some other reasons lay on measurement errors due to bid-ask spread, non-synchronous trading and liquidity as reported by Park (1995), Ball et al. (1995), Conrad et al. (1997).

Lastly, for better understanding the composition of contrarian profits Lo and MacKinlay (1990) developed decomposition model for the expected contrarian profits. The model could be used to quantify to what extent the profit is resulted from cross-sectional correlation and autocorrelation. However, as Chou et al. (2007) point out, that the length of forming and holding period could potentially affect the contrarian/momentum profits. The choices of the composition in the portfolio are determined by the formation period as past winners and past losers are chosen. The return of the portfolio then depends on the holding period selected, as evidenced by Jegadeesh and Timan (2001). However, the classic decomposition for the expected contrarian profits in Lo and MacKinlay (1990) and Jegadeesh and Timan (1995) only considers cases of symmetric lengths of formation and holding period. Chou et al. (2007) extend the decomposition method developed by Lo and MacKinlay (1990) by allowing unsymmetrical lengths. As far as we know, this model has never been applied in the China market, we therefore contributes to the literature by utilizing this advanced model from Chou et al. (2007) in our paper.

3. Data and Methodology

3.1 Data description

In this thesis, we obtain weekly stock returns[1] of Chinese "A" shares listed on both the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) from 2002 to 2011. These data are sourced from Thomson Reuters DataStream. The first week return of any newly listed company is eliminated because of the substantial underpricing and irregular returns in IPOs in China (see Sun and Tong, 2000), so that abnormal returns from IPOs would not influence our results. Our sample contains 2386 firms ever listed within the sample period. There were 1127 firms listed in the China stock market at the beginning of 2002 and 2369 firms with valid trading data at the end of 2011. Totally, it contains 521 weekly periods in overall sample.

In order to simulate the historical trading environment and avoid survivorship bias[2], we include non-active stocks that were delisted or suspended for some period. However, disappearing trades[3] are found due to various reasons, such as merger and acquisition, delisting or investigation on management issues. This may result in the problem of non-synchronous trading, a term describing a non-synchronous reactions to the same systematic news due to non-trading of some of the stocks. The treatment for non-synchronous trading will be discussed later in section 3.2. Also as the zero return figures may distort our stock formation process since zero returns cannot be ranked in between each other, we modify these zero returns into non-numeric data so that it will not be influencing our portfolio formation.

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[1] Stock return is based on total return index of each firm starting from Tuesday, January 2nd, 2002 and ends at Monday, December 28th, 2011. To calculate the weekly return, we apply continuously compounded method (logarithmic return). Total return index for each firm is including return adjusted by dividends, rights offering and other distributions.

[2] Survivorship bias occurs when failed companies (no longer exist or delisted) are excluded from the performance studies. Results from studies would become higher than the true value because only the successful companies are taken into account.

[3] Disappearing trades occur when trading volume equals zero, but stock's total return index remains the same as the previous period. Thus, stock's return remain zero based on the calculation.

Our data also include market capitalization (in thousands Yuan) and stock turnover by volume (in thousands time). Market capitalization is used for size-related lead-lag structure effect on contrarian profits. We are also interested in the question: whether any specific contrarian strategy may capture abnormal return in the global financial crises period. We divided the whole period into two subsamples: January 2nd, 2002 to August 9th, 2007, and August 10th, 2007 to November 2011, where the dividing point is the beginning of the global financial crisis represented by BNP Paribas' ceasing investment in US mortgage debt. The comparison between subsamples and entire sample may generate interesting results. The detail descriptive statistics are reported in **Table 1.**

Table 1. Descriptive statistics

	Weekly Stock Return	Turnover by Volume	Market Value
Overall sample	**From 2002-1-2 to 2011-12-28**		
Mean	-0.0031	34726.28	9567.57
Median	-0.0011	24031.40	8526.59
Skewness	-0.1493	2.25	0.57
Excess kurtosis	3.8520	9.19	0.36
Standard deviation	0.0699	36387.13	3939.64
Minimum	-1.0154	0	76
Maximum	2.7972	55608430	6475260
Average Observations	412	412	412
First subsample	**From 2002-1-1 to 2007-8-9**		
Mean	0.0030	19310.90	6688.92
Median	0.0028	12028.17	6242.13
Skewness	-0.3326	1.53	1.28
Excess kurtosis	5.4147	5.56	2.59
Standard deviation	0.0697	24424.58	2325.21
Minimum	-0.9808	0	76
Maximum	2.4923	55608430	1555966
Average observations	235	235	235
Second subsample	**From 2007-8-10 to 2011-12-28**		
Mean	-0.0040	42487.42	11225.83
Median	-0.0003	33370.00	10556.04
Skewness	-0.1489	1.94	0.29
Excess kurtosis	2.0670	6.40	-0.05
Standard deviation	0.0730	32921.53	3558.04
Minimum	-1.0154	0	76
Maximum	2.7972	8454702	6475260
Average observations	167	167	167

From above, all returns are negatively skewed and leptokurtic. Weekly stock return is averagely -0.3% in overall sample. Mean return (0.3%) in first subsample (so called ex ante crises period) is way higher than the one (-0.4%) in second subsample (so called crises period). Relatively higher standard deviation in second subsample (0.073) implies unusual risk embedded in this period. The turnover in second subsample (42487.42 thousands) is also the highest among the samples. The highest market capitalization (6475.26 million) is observed in the second subsample period. The different figures summarized in three samples may result in surprising finding for the contrarian and momentum profits.

To construct the Sharper-Lintner Capital Asset Pricing Model (CAPM) formed by Chan (1988) for testing time-varying market risk (discussed in Section 5.1), we need market risk factor. DataStream China "A" DS market index (weekly total return) is used as proxy for weekly market return. Weekly market return is computed with continuously compounded method. And China interbank one-week offered rate, obtained from DataStream as well, is used as risk free rate. Risk free rate data is transformed from annualized rate into weekly rate. Details related to the model will be illustrated in section 4.

3.2 Portfolios construction methodology

To test the existence of momentum and contrarian profits. Portfolios are formed based on the methodology employed in Lo and MacKinlay (1990), Jegadeesh and Titman (1993), Jegadeesh and Titman (1995), and closely to Kang et al. (2002). At the beginning of each week t, all stocks are ranked based on their returns from the previous F-week formation period in an ascending order. Five equal-size quintiles portfolios are then formed and each portfolio's equal-weighted average return for F-week period is computed. The portfolio with highest equal-weighted average returns is defined as the winner portfolio and the lowest is defined as the loser portfolio. The quintiles in between the loser and winner portfolios are given number orders in ascending order (2, 3, 4), but they are not examined in our thesis. Nine formation periods are taken into considerations, thus F=1, 2, 4, 8, 12, 16, 20, 26, 52 in terms of weeks. Notice that we require stocks to be listed, namely stocks should have valid return so that they can be identified as winners or losers[4].

Each equal-size quintile portfolio under various formation periods is continued to be held for H weeks (H refers to holding period). We consider using the same horizons in the formation period as in the holding period, thus H=1, 2, 4, 8, 12, 16, 20, 26, 52. By then, a spectrum of F-H strategy is formed. In general we have 81 (9x9) different investment strategies. Equal-weighted average portfolio return for holding period generated from each quintile is what we attempt to compare between winner portfolios and loser portfolios for each F-H strategy. The difference between the returns of winner and the loser portfolio is namely the profit from buying winner and selling loser, which constructs the momentum strategy. If the difference in holding period return is significantly different from zero and it is positive, we can conclude that momentum profits exist. And if it is significantly negative, then it implies contrarian strategy is profitable. In addition, following the design of Kang et al. (2002), we employ overlapping data to increase our test power (Jegadeesh and Titman, 1993). For example, when constructing 4-week return, the first return covers 1st week to 4th week and the second return covers 2nd week to 5th week, and so on.

To avoid the possible measurement error that may arise from bid-ask spread, price pressure due to illiquid markets, and non-synchronous data, one trading day between portfolio formation and holding periods for all investment strategies is skipped (Kang et al., 2002; for similar treatment, see Chan et al., 1999; Lehmann, 1990). For instance in the formation period, a week may begin on Tuesday and ends on the following Wednesday (if the Wednesday is not a trading day, then the next trading date is used). Subsequently for the holding period, a week begins on Wednesday and ends on Thursday (if Wednesday is not a trading day, then we will use the next trading day).

[4] If return equals zero due to disappearing trades, which has been transformed into non-numeric data, this stock would not be taken into the ranking process at time t.

4. Profitability of Momentum and Contrarian Strategies

Table 2 reports the profitability of 81 equal-weighted zero investment strategies for overall sample. The table consists of 9 parts, differing by the 9 formation periods. The first two rows of each part report the return of winner stocks followed by the loser stocks during the holding period. Then the W-L row reports the profit from buying winners stocks and selling losers stocks for 9 different holding periods during the investigating period. The t-statistics are also reported for the profitability figure of each strategy. If the profit from W-L is positive and significant, there exists momentum profit. If it is negative and significant, then it is contrarian profit.

For the overall sample from 2002 to 2011, the average return of the loser portfolio is larger than that of the winner portfolio. Among the 81 strategies, 19 strategies have negative profits (1-1, 4-4, 4-8,4-12, 8-1, 8-2, 8-4, 8-8, 8-12, 8-16, 12-1, 12-2, -12-4, 12-8, 12-12, 16-4, 16-8, 20-4 and 20-8) that are statistically significant different from zero. As a result, all the 19 strategies are contrarian strategies. The 19 strategies are located within 6 formation periods (1-H, 4-H, 8-H, 12-H, 16-H and 20-H) and 6 holding periods (F-1, F-2, F-4, F-8, F-12 and F-16), indicating the existence of short- and intermediate-term contrarian profits. The results are a bit different from Kang et al. (2002), where they find short-term contrarian and intermediate-term momentum profits in the China "A" share market from 1993 to 2000.

Table 2. Contrarian profitability summery for overall sample

Strategy	1-1	1-2	1-4	1-8	1-12	1-16	1-20	1-26	1-52
Winner	-0.0158	-0.0049	-0.0044	-0.0022	-0.0011	-0.0003	0.0004	0.0013	0.0031
Loser	0.0064	0.0009	0.0023	0.0034	0.003	0.003	0.0034	0.0035	0.0037
W-L	-0.0221	-0.0059	-0.0067	-0.0056	-0.0042	-0.0033	-0.003	-0.0022	-0.0006
t-stat.	-1.8510*	-0.6864	-1.0517	-1.2442	-1.0488	-0.9305	-0.9094	-0.7147	-0.2612
Std W	0.0473	0.2176	0.4665	0.683	0.8264	0.9091	0.9535	0.9765	0.9882
Std L	0.0491	0.2216	0.4707	0.6861	0.8283	0.9101	0.954	0.9767	0.9883
F stat.	0.9300	0.9453	0.9805	1.0052	0.9642	0.9772	0.9398	0.9685	0.9920
Strategy	**2-1**	**2-2**	**2-4**	**2-8**	**2-12**	**2-16**	**2-20**	**2-26**	**2-52**
Winner	-0.0077	-0.0028	-0.0047	-0.0033	-0.0018	-0.0007	-0.0003	0.0008	0.003
Loser	0.0038	0.0005	0.0029	0.004	0.0033	0.0028	0.0031	0.003	0.0035
W-L	-0.0114	-0.0033	-0.0076	-0.0073	-0.0051	-0.0035	-0.0034	-0.0022	-0.0005
t-stat.	-0.9554	-0.3888	-1.1953	-1.6003	-1.2853	-0.9717	-1.0128	-0.7065	-0.2174
Std W	0.0466	0.2158	0.4645	0.6816	0.8256	0.9086	0.9532	0.9763	0.9881
Std L	0.0498	0.2231	0.4724	0.6873	0.829	0.9105	0.9542	0.9768	0.9883
F stat.	0.8749	0.8571**	0.9079	0.9797	0.9386	0.9464	0.9061	0.9506	0.9779
Strategy	**4-1**	**4-2**	**4-4**	**4-8**	**4-12**	**4-16**	**4-20**	**4-26**	**4-52**
Winner	-0.0096	-0.007	-0.0082	-0.0052	-0.0031	-0.0018	-0.0011	0.0003	0.0028
Loser	0.0079	0.0057	0.0072	0.0057	0.0044	0.0037	0.0039	0.0034	0.0037
W-L	-0.0176	-0.0127	-0.0154	-0.0109	-0.0075	-0.0055	-0.005	-0.0031	-0.0009
t-stat.	-1.4528	-1.4973	-2.4252**	-2.4008**	-1.9045*	-1.5415	-1.4973	-1.0103	-0.3775
Std W	0.0469	0.2165	0.4652	0.6821	0.8259	0.9088	0.9533	0.9764	0.9881
Std L	0.0504	0.2244	0.4737	0.6883	0.8296	0.9108	0.9544	0.9769	0.9884
F stat.	0.8652	0.8554**	0.9059	0.9551	0.8928	0.8871	0.8542 **	0.9000	0.9521
Strategy	**8-1**	**8-2**	**8-4**	**8-8**	**8-12**	**8-16**	**8-20**	**8-26**	**8-52**
Winner	-0.011	-0.0085	-0.0083	-0.0053	-0.0033	-0.0021	-0.0012	0.0001	0.0028
Loser	0.0113	0.009	0.0075	0.0056	0.004	0.0038	0.0035	0.0031	0.0037
W-L	-0.0223	-0.0175	-0.0158	-0.0108	-0.0073	-0.006	-0.0047	-0.0031	-0.0009
t-stat.	-1.827*	-2.0545**	-2.4767**	-2.3696**	-1.8270*	-1.6523*	-1.4062	-0.9766	-0.3606
Std W	0.0468	0.2164	0.4652	0.682	0.8259	0.9088	0.9533	0.9764	0.9881
Std L	0.0507	0.2251	0.4744	0.6888	0.8299	0.911	0.9545	0.977	0.9884
F stat.	0.8545**	0.8099**	0.8317**	0.8629	0.8248**	0.7908**	0.7935**	0.8448**	0.9132
Strategy	**12-1**	**12-2**	**12-4**	**12-8**	**12-12**	**12-16**	**12-20**	**12-26**	**12-52**
Winner	-0.0104	-0.0078	-0.0074	-0.0043	-0.0029	-0.0018	-0.0009	0.0002	0.003
Loser	0.01	0.0078	0.007	0.0047	0.0041	0.0036	0.0032	0.003	0.0039
W-L	-0.0204	-0.0156	-0.0144	-0.009	-0.007	-0.0055	-0.0041	-0.0028	-0.0009
t-stat.	-1.6568*	-1.8135*	-2.2245**	-1.9341*	-1.7248*	-1.4993	-1.2020	-0.8944	-0.3617
Std W	0.0475	0.218	0.4669	0.6833	0.8266	0.9092	0.9535	0.9765	0.9882
Std L	0.0506	0.2249	0.4742	0.6886	0.8298	0.911	0.9544	0.977	0.9884
F stat.	0.8828	0.8198**	0.8200**	0.8253**	0.7730**	0.7651**	0.7631**	0.8256**	0.9074
Strategy	**16-1**	**16-2**	**16-4**	**16-8**	**16-12**	**16-16**	**16-20**	**16-26**	**16-52**
Winner	-0.0082	-0.0064	-0.006	-0.0038	-0.0026	-0.0014	-0.0006	0.0007	0.0032
Loser	0.0091	0.0066	0.0059	0.0048	0.0037	0.0032	0.003	0.0028	0.004
W-L	-0.0174	-0.013	-0.0119	-0.0086	-0.0063	-0.0045	-0.0036	-0.0021	-0.0008
t-stat.	-1.3981	-1.4901	-1.7953*	-1.8202*	-1.5357	-1.2279	-1.0524	-0.6566	-0.3289
Std W	0.0477	0.0662	0.0991	0.1401	0.1783	0.2128	0.2469	0.3046	0.5519
Std L	0.0506	0.0726	0.1096	0.1571	0.2051	0.2467	0.2847	0.3388	0.582
F stat.	0.8881	0.8313**	0.8174**	0.7961**	0.7555**	0.7438**	0.7508**	0.8083**	0.9101
Strategy	**20-1**	**20-2**	**20-4**	**20-8**	**20-12**	**20-16**	**20-20**	**20-26**	**20-52**

Winner	-0.0075	-0.0059	-0.0056	-0.0035	-0.0022	-0.0012	-0.0002	0.0012	0.0033
Loser	0.0094	0.0077	0.0069	0.0047	0.0035	0.0032	0.003	0.0028	0.0043
W-L	-0.0169	-0.0137	-0.0125	-0.0082	-0.0057	-0.0043	-0.0032	-0.0016	-0.001
t-stat.	-1.3615	-1.5526	-1.8866*	-1.7386*	-1.3813	-1.1639	-0.9173	-0.5025	-0.3759
Std W	0.0478	0.066	0.0989	0.1394	0.1777	0.2134	0.2482	0.3054	0.4827
Std L	0.0507	0.073	0.1101	0.1576	0.2063	0.2481	0.2867	0.34	0.5043
F stat.	0.8886	0.8171**	0.8066**	0.7820**	0.7425**	0.7396**	0.7492**	0.8068**	0.9160
Strategy	**26-1**	**26-2**	**26-4**	**26-8**	**26-12**	**26'-16**	**26-20**	**26-26**	**26-52**
Winner	-0.0066	-0.0055	-0.0052	-0.0032	-0.0017	-0.0004	0.0007	0.002	0.0036
Loser	0.0079	0.006	0.0049	0.0038	0.0032	0.0029	0.0028	0.0033	0.0049
W-L	-0.0145	-0.0115	-0.0101	-0.007	-0.005	-0.0034	-0.0021	-0.0012	-0.0013
t-stat.	-1.1640	-1.2973	-1.5166	-1.4554	-1.1858	-0.8913	-0.6063	-0.3793	-0.4993
Std W	0.0475	0.0658	0.0985	0.1402	0.1805	0.2173	0.2528	0.3101	0.4885
Std L	0.0505	0.0727	0.11	0.1584	0.2078	0.2512	0.2888	0.341	0.506
F stat.	0.8845	0.8180**	0.8025**	0.7840**	0.7543**	0.7480**	0.7661**	0.8270**	0.9320
Strategy	**52-1**	**52-2**	**52-4**	**52-8**	**52-12**	**52-16**	**52-20**	**52-26**	**52-52**
Winner	-0.0022	-0.0017	-0.0017	-0.0005	0.0002	0.0008	0.0014	0.002	0.0041
Loser	0.0099	0.0078	0.0068	0.006	0.0058	0.0057	0.0059	0.0062	0.0075
W-L	-0.0121	-0.0095	-0.0085	-0.0065	-0.0056	-0.0049	-0.0045	-0.0042	-0.0034
t-stat.	-0.9236	-1.0198	-1.2122	-1.2852	-1.2670	-1.2208	-1.2225	-1.2072	-1.2734
Std W	0.0477	0.0668	0.1013	0.145	0.1889	0.2284	0.2655	0.326	0.5079
Std L	0.0524	0.0752	0.1129	0.1621	0.2103	0.2516	0.289	0.326	0.5056
F stat.	0.8303**	0.7898**	0.8062**	0.8005**	0.8064**	0.8235**	0.8443**	0.9033	1.0092

Note: all returns are normalized to one-month return for comparison purpose.

T-test is conducted for two sample (W and L) means with hypothesis that two means are equal.

F-test is conducted for two sample (W and L) variances with hypothesis that two variance are equal.

**Significance at 5% level and lower

*Significance at 10% level

6 out of the 19 strategies are significant at 5% level. For 4-H strategies, 4-4 and 4-8 are statistically significant at 5% level. For 8-H strategies, 8-2, 8-4 and 8-8 are statistically significant. For 12-H, only 12-4 is statistically significant. The results show that the most significant contrarian profits cluster around short and intermediate-term formation and holding periods. The result is consistent with Kang et al. (2002) that the 5% statistically significant contrarian profits are found in short to intermediate-term formation and holding periods. However, unlike Kang et al. (2002), which also report higher profits for longer holding periods from 1993 to 2000, our result shows no such pattern emerging. The magnitude of contrarian profits is from 0.6% to 2.2%, and average profit is 1.1%. Also, it is observed that for fixed formation period, contrarian profit decreases as the holding period becomes longer. We also conduct F-test for comparing the variances between winner portfolio and loser portfolio. It is interesting to notice that among

the 19 strategies found to be profitable, 13 strategies are tested to have statistically significant different variance between winner and losers. This implies that the different risks between winner and loser may be the reason for the variation in returns.

The overall sample is divided into two subsamples, and the profitability results for subsamples and overall sample are summarized in **Appendix**. The full sample figures are then followed by the first subsample and the second subsample with similar layout. In total 243 strategies are reported, with 81 for each subsample. The investigation of the sample period before the financial crisis (from January 2002 to August 2007) reveals a distinct pattern from the full sample. Among the 81 strategies, 10 (4-4, 4-8, 8-4, 8-8, 12-4, 16-52, 20-52, 26-26, 26-52 and 52-52) are statistically significant. 5 out of the 10 are contrarian and the other 5 are momentum. The contrarian strategies are distributed among three short- to intermediate-term formation periods (4-H, 8-H and 12-H) and two short-term holding periods (F-4 and F-8). The five momentum profits cluster around three intermediate- to long-term formation periods (20-H, 26-H and 52-H) and two intermediate- to long-term holding periods (F-26 and F-52). The result is similar to that from Kang et al. (2002) as mentioned above. However, Kang et al. (2002) also document higher average contrarian profits than momentum profits, while our figure does not reveal similar pattern. Of all the 10 strategies, only the profits of 8-4 (contrarian) and 26-52(momentum) strategies are significant at 5% level.

Subsample 2 studying the period during the global financial crisis (from August 2007 to December 2011) has yielded eight statistically significant strategies and they are all contrarian strategies (4-4, 26-52, 52-8, 52-12, 52-16, 52-20, 52-26 and 52-52). They are from three formation periods (4-H, 26-H and 52-H) and seven holding periods (F-4, F8, F-12, F-16, F-20, F-26 and F-52). Noticeably, six out of the eight contrarian profits come from formation period of 52 weeks. A big distinction from what Kang et al. (2002) has found out, most of the contrarian strategies from after the financial crisis are intermediate- to long-term strategies. six out of eight contrarian profits are statistically significant at 5% level (26-52, 52-12, 52-16, 52-20, 52-26 and 52-52). It indicates that the longer the formation period, the more probable that it is going to yield significant contrarian profits.

The comparison of the full sample, subsample 1 and subsample 2 reveals that the profit strategies within subsample 1 and subsample 2 are very different and they are in turn quite distinct from those of the full sample. There is only one strategy (4-4) that generates consistently contrarian profit during all the three periods. 5 contrarian strategies (4-4, 4-8, 8-4, 8-8 and 12-4) overlap between full sample and subsample 1 (before the financial crisis). No strategies are found to be overlapping between full sample and subsample 2 as well as between subsample 1 and subsample 2. The migration of contrarian profits from short- and intermediate-term formation periods to long-term formation periods could possibly indicate that the Chinese investors are moving towards longer investment horizon and are increasingly looking for value stocks. The shift could also imply that there is an on-going regime shift such as stricter regulations in the China market after the financial crisis or that the underlying risk of the market has been changing.

5. Alternative sources of contrarian profits

Recall the discussions in section 1, contrarian profits obtained in China stock market may due to several sources. Firstly, measurement error has been controlled by skipping one day between formation period and holding period. Second, time-varying market risk can be used to argue that losers contain higher risk than winners so as to capture higher returns. Third, overreaction to firm specific information may contribute to the reversal effect. Lastly, size-related lead-lag structure in stock returns may be an alternative to overreaction hypothesis. In section 5.3 we will test both overreaction hypothesis and lead-lag effect by constructing autocorrelation matrix.

5.1 Robustness to time-varying market risk

Contrarian strategies generating abnormal profits by simply buying loser and selling winner is a violation of week-form EMH. An interpretation for the evidence was introduced by Chan (1988), who documented non-constant risk over time between loser stocks and winner stocks as an explanation for abnormal profit. When risk changes are adjusted for the returns, profitability on contrarian strategies become reasonably small. The basic idea he concluded for contrarian profits is that losers tend to be riskier than winner in holding period. We follow Kang et al. (2002) using a simplified model from Chan (1988) below to investigate the significance of time-varying market risk to contrarian profits.

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \varepsilon_t \qquad p \in (W, L) \tag{1}$$

For winner portfolio:

$$r_{Wt} - r_{ft} = \alpha_W + \beta_W(r_{mt} - r_{ft}) + \varepsilon_{Wt} \tag{1a}$$

For loser portfolio:

$$r_{Lt} - r_{ft} = \alpha_L + \beta_L(r_{mt} - r_{ft}) + \varepsilon_{Lt} \tag{1b}$$

Equation (1b)-(1a):

$$r_{Lt} - r_{Wt} = \alpha^c + \beta^c(r_{mt} - r_{ft}) + \varepsilon_t^c \tag{2}$$

Where r_{pt} is the portfolio holding period return at time t, r_{Wt} and r_{Lt} are winner and loser portfolios return respectively. r_{ft} is the risk-free rate at time t, r_{mt} is the market index[5] return at time t, $r_{mt} - r_{ft}$ is the market risk premium at time t, α and β are the intercept and slope (market beta) coefficients. The superscripts "c" refers to contrarian strategies. If the betas are significantly different from zero for equation (2), namely winner portfolio and loser portfolio has different market risk, we conclude that market risk contributes to abnormal returns in these contrarian strategies. We use this model to examine the 19 profitable contrarian strategies in overall sample. Results are reported in **Table 3**.

Table 3. Robustness check for time-varying market risk

	α		β		R2
Full Sample (19 strategies)					
Strategy (1-1)					
Winner	-0.0048	(-3.1797) ***	0.8414	(21.6035) ***	0.474
Loser	0.0007	(0.4717)	0.9094	(23.4492) ***	0.5149
Loser-Winner	0.0055	(5.8751) ***	0.068	(2.8121) ***	0.015
Strategy (4-4)					
Winner	-0.0125	(-4.9813) ***	1.0018	(32.4139) ***	0.6724
Loser	0.0029	(0.9911)	0.9908	(27.4801) ***	0.5959
Loser-Winner	0.0155	(7.5866) ***	-0.011	(-0.4416)	0.0004
Strategy (4-8)					
Winner	-0.0194	(-5.5282***)	0.997	(34.1002***)	0.696
Loser	0.0026	(0.6326)	0.9587	(28.4764***)	0.6148
Loser-Winner	0.022	(8.5973***)	-0.0382	(-1.7978*)	0.0063
Strategy (4-12)					
Winner	-0.0225	(-5.1547***)	0.9776	(35.704***)	0.7167
Loser	-0.0001	(-0.0126)	0.9998	(31.9666***)	0.6697
Loser-Winner	0.0224	(8.0935***)	0.0223	(1.2805)	0.0032
Strategy (8-1)					
Winner	-0.0037	(-2.5126)**	0.8621	(22.9522)***	0.5076
Loser	0.0019	(1.1758)	0.9135	(22.0297)***	0.4871
Loser-Winner	0.0055	(5.1949)***	0.0514	(1.8661)*	0.0068
Strategy (8-2)					
Winner	-0.0062	(-3.502)***	0.9112	(29.0071)***	0.6226
Loser	0.0026	(1.2089)	0.955	(25.172)***	0.5541
Loser-Winner	0.0087	(6.037)***	0.0438	(1.6964)*	0.0056
Strategy (8-4)					
Winner	-0.0122	(-5.1775)***	1.0006	(34.6011)***	0.7021
Loser	0.0036	(1.1821)	0.9961	(26.4308)***	0.579
Loser-Winner	0.0159	(7.7829)***	-0.0045	(-0.1816)	0.0001
Strategy (8-8)					
Winner	-0.0189	(-5.6033)***	0.9791	(34.9068)***	0.7074

[5] see section 2.

Loser	0.0027	(0.6466)	0.9808	(28.2555)***	0.613
Loser-Winner	0.0217	(8.4278)***	0.0017	(0.0784)	0.
Strategy (8-12)					
Winner	-0.0224	(-5.2306)***	0.9587	(35.7633)***	0.7189
Loser	-0.001	(-0.2009)	1.0199	(31.9921)***	0.6718
Loser-Winner	0.0214	(7.7475)***	0.0612	(3.5423)***	0.0245
Strategy (8-16)					
Winner	-0.0259	(-5.2849)***	0.9447	(37.7155)***	0.7415
Loser	-0.0031	(-0.5304)	1.0395	(34.9225)***	0.7109
Loser-Winner	0.0228	(7.8301)***	0.0948	(6.3667)***	0.0755
Strategy (12-1)					
Winner	-0.0089	(-4.4262)***	0.0973	(7.6875)***	0.1044
Loser	-0.0038	(-1.7635)*	0.0959	(7.0639)***	0.0896
Loser-Winner	0.0051	(4.5828)***	-0.0015	(-0.21)	0.0001
Strategy (12-2)					
Winner	-0.011	(-4.2713)***	0.1928	(11.8904)***	0.2184
Loser	-0.0032	(-1.0975)	0.1926	(10.5041)***	0.179
Loser-Winner	0.0078	(5.0519)***	-0.0002	(-0.0202)	0.
Strategy (12-4)					
Winner	-0.0159	(-4.5368)***	0.3732	(17.0157)***	0.3649
Loser	-0.0015	(-0.3644)	0.3778	(14.9552)***	0.3074
Loser-Winner	0.0144	(6.4998)***	0.0046	(0.3282)	0.0002
Strategy (12-8)					
Winner	-0.0191	(-4.6515)***	0.6679	(25.9757)***	0.5744
Loser	-0.0012	(-0.2547)	0.6855	(22.3685)***	0.5002
Loser-Winner	0.0179	(6.2554)***	0.0175	(0.9805)	0.0019
Strategy (12-12)					
Winner	-0.0217	(-5.0938)***	0.9466	(35.586)***	0.7186
Loser	-0.0016	(-0.3049)	1.0412	(31.9514)***	0.673
Loser-Winner	0.0201	(6.8099)***	0.0946	(5.1299)***	0.0504
Strategy (16-4)					
Winner	-0.0161	(-4.2447)***	0.2687	(13.7844)***	0.2758
Loser	-0.0044	(-1.0179)	0.2767	(12.5529)***	0.24
Loser-Winner	0.0118	(4.9131)***	0.008	(0.6534)	0.0009
Strategy (16-8)					
Winner	-0.0204	(-4.5074)***	0.5051	(21.8965)***	0.492
Loser	-0.0036	(-0.695)	0.5462	(20.5087)***	0.4594
Loser-Winner	0.0167	(5.6406)***	0.0411	(2.7145)***	0.0147
Strategy (20-4)					
Winner	-0.0179	(-4.6199)***	0.2183	(12.9448)***	0.2525
Loser	-0.0057	(-1.3018)	0.236	(12.4907)***	0.2393
Loser-Winner	0.0123	(4.9546)***	0.0177	(1.6483)*	0.0054
Strategy (20-8)					
Winner	-0.0217	(-4.5269)***	0.3985	(19.1585)***	0.4273
Loser	-0.0058	(-1.0579)	0.4398	(18.4404)***	0.4087
Loser-Winner	0.0159	(5.2143)***	0.0413	(3.1266)***	0.0195

Note: t-statistics are in the parentheses.

* Significance level at 10%;

**Significance level at 5%;

***Significance level at 1%.

Tests results show that 14 out of the 19 strategies have positive betas. The rest with negative betas are strategies 4-4, 4-8, 8-4, 12-1, 12-2. But only 10 out of the 19 betas are significantly different from zero, they are strategies: 1-1, 4-8, 8-1, 8-2, 8-12, 8-16, 12-12, 16-8, 20-4, 20-8. The betas vary from 0.0177 to 0.0948. The majority strategies are profitable under the higher risk on loser stocks. Also, betas become larger when either formation or holding period gets longer. For example, strategy 8-16 and 12-12 have highest betas close to 0.095. It implies that intermediate contrarian strategies profits are easily influenced by time-varying market risk. However, betas are not the only explanation for contrarian profits. All the alphas are statistically significantly different from zero and are positive, indicating that there are more factors to explain contrarian profits.

5.2. Overreaction to firm-specific information and lead-lag structure effect in stock returns

DeBondt and Thaler (1985) illustrate that overreaction effect is the cause of negative serial autocorrelation of individual securities. They highlight that extreme movement in stock prices will lead to opposite directional movements later on. Besides that, Lo and MacKinlay (1990) report that positive cross-serial autocorrelations are found between the returns of small stocks and the lagged returns of large stocks, denoting that size-related lead-lag structure in stock returns also contributes to the contrarian profits. Overreaction (serial autocorrelation) and lead-lag structure (cross-sectional autocorrelations) are widely considered as two of the most important sources of contrarian profits. In order to examine whether overreaction hypothesis and lead-lag structure are the main contributions to our contrarian profits, we follow the method adopted by Kang et al. (2002) to sort our full sample into five quintile size-level portfolios based on their market capitalization at time t. The size-sorted portfolios are S1 (smallest firms), S2, S3, S4 and S5 (largest firms) in an ascending order of firm size measured, and time t is the initial of every strategy formation time. As we are using overlapping return data, size-sorting process is conducted from time to time. For the 19 strategies tested to be profitable, we wonder whether it is the overreaction effect or the size related lead-lag structure that contributes to the abnormal return. We construct own-serial autocorrelations and cross-serial autocorrelations for stock returns on holding period of five size-sorted quintile portfolios and report them in **Table 4**.

Table 4. Own-serial and cross-serial correlations of size-sorted portfolio returns for contrarian strategies

	1-1	**4-4**	**4-8**	**4-12**	**8-1**
S1-Lagged S1	0.0671	0.1084**	0.1985**	0.213**	0.0498
S1-Lagged S5	0.082	0.1227**	0.3033**	0.3649**	0.0737
S5-lagged S1	-0.0552	0.0525	0.1873**	0.2325**	-0.0659
S5-Lagged S5	0.0088	0.066	0.3012**	0.3808**	0.0059
	8-2	**8-4**	**8-8**	**8-12**	**8-16**
S1-Lagged S1	0.1539**	0.0989**	0.2043**	0.2106**	0.2109**
S1-Lagged S5	0.1858**	0.1133**	0.3071**	0.3644**	0.3464**
S5-lagged S1	0.0705	0.0464	0.1887**	0.2275**	0.2485**
S5-Lagged S5	0.1665**	0.065	0.3069**	0.3798**	0.374**
	12-1	**12-2**	**12-4**	**12-8**	**12-12**
S1-Lagged S1	0.0466	0.1523**	0.101**	0.2043**	0.2111**
S1-Lagged S5	0.0689	0.1901**	0.115**	0.3081**	0.3687**
S5-lagged S1	-0.0648	0.0796	0.0432	0.1854**	0.2252**
S5-Lagged S5	0.0071	0.175**	0.0658	0.3065**	0.3813**
	16-4	**16-8**	**20-4**	**20-8**	
S1-Lagged S1	0.0984**	0.2056**	0.1028**	0.2042**	
S1-Lagged S5	0.1098**	0.3107**	0.1168**	0.3138**	
S5-lagged S1	0.0412	0.1887**	0.0514	0.1884**	
S5-Lagged S5	0.0666	0.3123**	0.0784	0.3155**	

Table 4 reports autocorrelations and cross-serial correlations for holding period returns of size-sorted portfolios based on the 19 contrarian strategies that we found significant in overall sample period. For example, for 4-8 strategy stocks are formed into five size-sorted portfolios at the initial of four-week formation period, then eight-week holding period return is collected for correlations test. For each contrarian strategies, we present only four essential correlations. S1-lagged S1 and S5-lagged S5 provide the one holding period lag (e.g. 4-8 strategy with holding period of 8 weeks takes 8-week lag) own- serial correlations between holding period returns of smallest stocks (S1) and largest stock (S5). S1-lagged S5 provides the cross-serial correlations between holding period returns of smallest stocks (S1) and lagged returns of largest stocks (S5). S5-lagged S1 provides the correlation between holding period returns of largest stocks (S5) and lagged returns of smallest stocks (S1). Since the observations vary from 482 (strategy 8-16) to 520 (strategy 1-1) due to weekly overlapping, we assume the data is under normal distribution and use Pearson correlation coefficient. T-tests under 5% significance level are conducted and results represented by **.

Among the 19 strategies, all the 38 own-serial autocorrelations are positive, and of which 28 correlations are significant under 5% significance level. It shows that within the same size group, the dominance of positive own-serial autocorrelations indicates an underreaction effect to firm-specific information, but not overreaction as documented by Kang et al. (2002). Though this result is inconsistent with previous findings, we explain the reasons to be the following: Kang et al. (2002) sorted the five size quintile portfolios at the initial of formation time, namely that stocks within the same size group would not be altered as time passes. The negative own-serial autocorrelation is examined existing in individual security level. However, we simulate the real trading world and sort the market capitalization of stocks before each time we form the portfolio. In fact, each size quintile's return is more closed to the market index return and shows large positive serial autocorrelation[6].Therefore, we suggest that if portfolios are constructed from time to time with different component stocks, overreaction effect is not a contribution to contrarian strategies.

Among the 38 cross-serial autocorrelations, only three of them are negative and insignificantly different from zero. This suggests that positive cross-serial autocorrelations dominate our sample, indicating that leading stocks with high return will follow by lagged stocks in the same direction, making contrarian strategies profitable when leading stocks are shorted and lagged stocks are longed. We notice that only 1-1, 8-1, and 12-1 strategies have not significant small-lead-large autocorrelations. For the remaining strategies varying from short-term period to intermediate period, small-lead-large has a materially higher autocorrelation magnitude (averagely 0.2189) than large-lead-small (averagely 0.1094). This suggests that smallest stocks are still leading large stocks in China stock market. The existence of positive cross-serial autocorrelation in stock portfolios gives rise to the conclusion that size-related lead-lag structure contributes to contrarian strategies, and the unique characteristics that small stocks lead large stocks still exist and is consistent with the findings from Kang et al. (2002). A reason for such leading direction may be boiled down to the fact that manipulating the sentiment in small stocks is much easier by the syndicate speculators as discussed in previous section. The dominance of individual

[6] Market index return is firstly found to be positively autocorrelated in the US market, according to Lo and Mackinlay (1988)

investors in the stock market is also a force, that less rational and educated investors become followers who facilitate the sentiment.

6. Decomposition of the contrarian profits

A framework for decomposing the expected contrarian profits was first adopted in Lo and MacKinlay (1990). The Lo and MacKinlay (1990) framework, and the other decomposition models based on this framework, such as Jegadeesh and Titman (1995) and Conrad and Kaul (1998), all assume symmetric lengths of formation (ranking) and holding periods. However, the lengths of the formation and holding periods could have be crucial for the contrarian strategies, given that winners and losers are ranked and selected in the formation periods and the returns are generated in the holding periods. To investigate the full spectrum of sources of the contrarian profits across various formation and holding periods, Chou et al. (2007) extend the framework by Lo and MacKinlay (1990) to asymmetric lengths of formation and holding periods and apply it on examination of the Japanese stock market. In this section we are going to apply the extended decomposition model from Chou et al. (2007) into the 19 contrarian strategies we document in the full sample.

The model is explained firstly with the introduction of some notions. Let $R_i(t,t+k)$ be the holding period return of stock i ($i=1,2,3,...,N$) from time t to time $t+k$ ($k=1,2,3,....$), and $R_{it}=R_i(t-1,t)$ be the one-period[7] return generated from $t-1$ to t. Also we denote $R(t,t+k)$ to be a $N\times 1$ column vector for a collection of returns of N individual stocks and $R_t = R(t-1,t)$ to be the column vector of one-period returns from time $t-1$ to time t. The mean of R_t is referred to as μ, and its k-th order autocovariance matrix as $\Gamma_k = E[(R_{t-k}-\mu)(R_t-\mu)'], k \geq 0$. Therefore, an "market portfolio" formed by all stocks with equal weights will be shown exactly as below:

$$R_{m,t} = R_m(t-1,t) = \frac{1}{N}\sum_{i=1}^{N} R_i(t-1,t) = \frac{1}{N}\boldsymbol{1}'\ R(t-1,t) \tag{3}$$

where $\boldsymbol{1}$ is a column vector of ones. The expected one-period return of the market portfolio is therefore $\mu_m = \frac{1}{N}\ \boldsymbol{1}'\mu$ and its k[th] order autocovariance is $\frac{1}{N^2}\boldsymbol{1}'\Gamma_k\boldsymbol{1}$.

[7] According to Chou et al. (2007), "one-period" could be 1 week or 2 weeks or any time periods, depending on the purpose of the research. But in our research, it represents one week.

The above notions are used to extend Lo and MacKinlay (1990) framework to allow for asymmetric lengths of formation and holding periods. The p-period return of the equally weighted market portfolio is written as follows:

$$R_m(t-p,t) = \frac{1}{N_t}\sum_{i=1}^{N_t} R_i(t-p,t) = \frac{1}{N_t}\boldsymbol{1'}R(t-p,t) \tag{4}$$

Eq. (4) differs from the Eq. (3) in that Eq. (3) is essentially a rebalanced equally weighted portfolio while Eq. (4) represents a buy-and-hold portfolio that assigns an equal weight to each component stock in the initial investment at time t-p and holds for p periods.

Let $w_{it}(p)$ be the weight invest on stock i, is denoted as below:

$$w_{it}(p) = -\frac{1}{N_t}\left[R_{it}(t-p,t) - R_m(t-p,t)\right] \tag{5}$$

Negative sign in the front means the stock is shorted. Under the contrarian strategy, a winner is determined and shorted when its previous return is lower than the previous market return. A loser is longed for opposite reason. The collection of the individual stock weights constructs a column vector $w_t(p) = (w_{it}(p),...,w_{Nt}(p))'$, and $w_t(p)$ could be rewritten as Eq. (6):

$$w_t(p) = -\frac{1}{N_t}R(t-p,t) + \frac{1}{N_t^2}\ \boldsymbol{1'}R(t-p,t)\boldsymbol{1} \tag{6}$$

The contrarian profit from a (p, q) strategy[8] can be shown in the following:

$$\pi_t(p,q) = w_t(p)'R(t,t+q)$$

$$= -\frac{1}{N_t}R(t-p,t)'R(t,T+p) + \frac{1}{N_t^2}\boldsymbol{1'}R(t-p,t)'R(t,T+p)\boldsymbol{1} \tag{7}$$

If $R_t(t,t+q)$, the q-period holding return is approximated by the simple sum of $\sum_{l=1}^{q} R_{t+1}$ (1 here represents a week). Then, Eq. (8) becomes:

[8] "p" represents formation period, and "q" represents holding period.

$$\pi_t(p,q) \approx -\frac{1}{N_t}\sum_{i=1}^{N}\left[\left(\sum_{l=0}^{p-1}R_{i,t-l}\right)\left(\sum_{l=1}^{q}R_{i,t+l}\right)\right] + \frac{1}{N_t^2}\sum_i\sum_j\left[\left(\sum_{l=0}^{p-1}R_{i,t-l}\right)\left(\sum_{l=1}^{q}R_{j,t+1}\right)\right] \quad (8)$$

Thus, the expected profit of a contrarian portfolio can be approximately decomposed to three components:

$$E(\pi_t(p,q)) = C_t(p,q) - O_t(p,q) - \sigma_t^2(p,q) \quad (9)$$

Where

$$C_t(p,q) = \frac{1}{N_t^{\,2}}\sum_i\sum_j{}_{i\neq j}\left[\sum_{l=0}^{p-1}(R_{i,t-1} - \hat{\mu}_i)\sum_{l=1}^{q}(R_{i,t+1} - \hat{\mu}_i)\right] \quad (9a)$$

$$O_t(p,q) = \frac{N_t - 1}{N_t^2}\sum_{i=1}^{N}\left[\sum_{l=0}^{p-1}(R_{i,t-l} - \hat{\mu}_i)\sum_{l=1}^{q}(R_{i,t+l} - \hat{\mu}_i)\right] \quad (9b)$$

$$\sigma_t^2(p,q) = \frac{pq}{N_t^2}\left(\sum_i\sum_j\hat{\mu}_i\hat{\mu}_j - N\sum_i\hat{\mu}_i^2\right)$$

(9c)

The three components are similar to Lo and MacKinlay (1990). The first term, $C_t(p,q)$, captures the cross-autocorrelations (also referred to as the "lead-lag effect") among individual stocks. A positive number of the term means that individual stocks have a tendency to follow the movement of the other stocks and will therefore contribute to the expected contrarian profit, and vice-versa. The second term, $O_t(p,q)$, refers to the average of the autocorrelations of all the individual stocks at time *t*. A negative $O_t(p,q)$ means that on average the individual stocks overreact to the information at time t and under-react if $O_t(p,q)$ is positive. Hence, a positive autocorrelation term would hurt the expected contrarian profit and hence it is put on a negative sign in Eq. (9). The last term $\sigma_t^2(p,q)$ is the cross-sectional variation in expected returns of individual stocks at time *t* and hence it is always positive. The contribution of the term to expected contrarian profit is therefore always negative.

As indicated in Eq. (9c), a contrarian strategy depends on the lengths of the formation and holding period. If the return-generating process is independently and identically distributed (i.i.d.) over time, the first term and the second term in

Eq. (9) will no longer exist. The expected profit of the contrarian portfolio then becomes $E(\pi_t(p,q)) = -O_t(p,q)$, and the per period holding return is:

$$\frac{E(\pi_t(p,q)}{q} = -\frac{p}{N^2}(\sum_i \sum_j \hat{\mu}_i \hat{\mu}_j - N\sum_i \hat{\mu}_i^2) \tag{10}$$

which depends only on the cross-sectional variation in individual returns along with lengths of the formation and holding horizons. This suggests that 1) the momentum strategy will be more profitable the longer the formation period and 2) if the returns of the stocks are i.i.d., there will only be momentum profit since the corss-sectional variation term will always be negative in Eq.(9).

Eq. (9) also implies that for a contrarian strategy to be profitable, the stock returns must exhibit time-series predictability. Only if the positive cross-autocorrelations and/or negative autocorrelations persistently dominate/dominates the cross-sectional variation will the contrarian strategy be profitable.

Table 5 presents the percentage of each of the three components ($C_t(p,q)$, $-\mathrm{O_t(p,q)}$ and $-\sigma_t^2(p,q)$ for the 19 full sample contrarian strategies. Columns A, B and C host the cross-autocorrelation, the autocorrelation and the cross-sectional variation term, respectively. Column D reports the sum from the cross-autocorrelation (Column A) and autocorrelation (Column B). It represents the proportion of the expected contrarian profit that is due to time-series predictability (i.e., $C_t(p,q) - O_t(p,q)$).

Table 5. Decomposition of the expected contrarian profits for the 19 contrarian strategies

Column	A	B	C	D
Strategies	Cross-Auto-correlation C(p,q)	Auto-correlation -O(p,q)	Cross-sectional variation -σ(p,q)	Time-Series predictability C(p,q)--O(p,q)
1-1	89.65%	10.53%	-0.18%	100.18%
4-4	73.72%	30.35%	-4.08%	104.08%
4-8	269.79%	-163.51%	-6.28%	106.28%
4-12	493.52%	-375.39%	-18.13%	118.13%
8-1	182.30%	-77.90%	-4.40%	104.40%
8-2	-113.52%	212.88%	0.64%	99.36%
8-4	228.44%	-122.79%	-5.65%	105.65%
8-8	300.92%	-193.43%	-7.49%	107.49%
8-12	323.02%	-213.63%	-9.39%	109.39%
8-16	122.44%	-21.64%	-0.80%	100.80%
12-1	252.11%	-146.40%	-5.71%	105.71%
12-2	-137.51%	236.52%	0.99%	99.01%
12-4	235.09%	-127.85%	-7.24%	107.24%
12-8	327.78%	-218.25%	-9.54%	109.54%
12-12	387.42%	-249.93%	-37.49%	137.49%
16-4	286.64%	-177.85%	-8.79%	108.79%
16-8	404.71%	-295.92%	-8.79%	108.79%
20-4	476.51%	-359.65%	-16.86%	116.86%
20-8	483.30%	-361.17%	-22.13%	122.13%
Average	246.65%	-137.63%	-9.02%	109.02%
Max	493.52%	236.52%	0.99%	137.49%
Min	-137.51%	-375.39%	-37.49%	99.01%

This table presents the decomposition of expected contrarian profits of the 19 contrarian strategies significant at 10% level. Column A reports the proportion attributable to cross-sectional autocorrelation (lead-lag relations). Column B shows the percentage accounted for by autocorrelations (overreaction/underreaction). Column C is the proportion in cross-sectional variation. Column D presents the proportion of the sum of cross-sectional autocorrelation and autocorrelation in total expected profits. It is also known as the component explainable by time-series predictability. Note the sum of the first three columns (A, B and C) is strictly 100%.

In order for contrarian strategy to be profitable, the sum of the cross-autocorrelation and autocorrelation term $C_t(p,q) - O_t(p,q)$ should be greater than the cross-sectional variation term. Among the 19 strategies we examine, 17 demonstrate stronger time-series predictability than cross-sectional variation (i.e.

they are expected to have contrarian profits). 2 strategies (8-2 and 12-2) are expected to have momentum profits. The average percentage of the sum of cross-autocorrelation and autocorrelation is 109.02%, and the cross-sectional variation therefore only accounts for -9.02% of the contrarian profits (or hurts 9.02% of the contrarian profit on average). The result confirms that contrarian strategies are the dominant strategies for the full data sample from 2002 to 2011 with the profit explainable by strong time-series predictability.

The fact that most of the contribution from the autocorrelation term ($-O_t(p,q)$) is negative is consistent with our previous finding that overreaction is not a source of contrarian profit. In general, under-reaction to firm specific information is profound and it is the biggest source to drag down contrarian profit. On the other hand, a dominant positive cross-autocorrelation suggests that lead-lag effect is the sole provider of expected contrarian profit. Also by comparing Column C and D, we found that the increase in the lengths of either formation or holding period leverages the effect of time-series predictability.

7. Conclusion

In this thesis we investigate the momentum/contrarian strategies in the China "A" share market from 2002 to 2011. 81 strategies from a combination of 9 different formation periods and 9 different holding periods (F, H=1, 2, 4, 8, 12, 16, 20, 26, 52) are examined. Our empirical results show that contrarian strategies are profitable on all the 81 strategies, and the most significant contrarian profits cluster around short-term and the intermediate-term, from 1 week to 20 weeks. Contrarian profits are up to 2.2% per month and decrease as holding period gets longer. We investigate into the two subsamples and it shows that momentum strategies are gradually losing ground to contrarian strategies over time, and contrarian profits are moving towards long-term-formation-period strategies after the financial crisis.

We conduct robustness tests to see if the three well-documented sources of contrarian profit: the time-varying market risk, overreaction effect and lead-lag structure can explain the contrarian profit we exploit earlier. The result from running the CAPM-like models indicates that time-varying market risk is one of the source contributes to contrarian strategy, but not a major one. Furthermore, the manipulation of the size-sorted portfolios suggest that overreaction is not a source of the contrarian profit and small stocks still lead large stocks in returns as consistent with the findings from Kang et al. (2002).

Lastly, the decomposition of the contrarian profits demonstrates that lead-lag effect is the sole provider of expected contrarian profit as compared to the US market whose contrarian profits are mostly attributed to overreaction. Our results indicate that 1) the Chinese "A" share market is similar to the Japanese market but distinct from the US market in terms of contrarian/momentum patterns; and 2) the market is more rational and the participants are more long-term oriented compared with 10 years ago.

The similarity in terms of abnormal profit between the Chinese market we examine and the Japanese market under the investigation of Chou et al. (2007) could stem from fact that the two markets have some fundamental similarities. While the widely practice of cross-holding in the Japanese market curb liquidity, the privatization of the Chinese state enterprises also leave a large amount of stock holdings untraded (as they are being hold in the hands of the state council that does not trade frequently). The Chinese and the Japanese are also considered as more collectivist than are Americans. Overconfidence and self-attribution bias are shown to be the major reason for momentum strategies to be profitable by Daniel et al. (1998). There are other reasons for the China "A" share market to exhibit the pattern we have reported. Such analysis is left for future work for researchers.

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Appendix

Profitability of momentum and contrarian strategies based on equal weighted portfolios for full sample, subsample 1and subsample 2

1-H	**1-1**	**1-2**	**1-4**	**1-8**	**1-12**	**1-16**	**1-20**	**1-26**	**1-52**
Full Sample									
W-L	-0.0220	-0.0058	-0.0067	-0.0057	-0.0042	-0.0033	-0.0030	-0.0022	-0.0006
t-stat.	-1.8510*	-0.6864	-1.0517	-1.2442	-1.0488	-0.9305	-0.9094	-0.7147	-0.2612
Subsample 1: Before the financial crisis									
W-L	-0.0151	-0.0014	-0.0067	-0.0050	-0.0031	-0.0031	-0.0030	-0.0019	0.0002
t-stat.	-1.0735	-0.1377	-0.6410	-0.9015	-0.6245	-0.6915	-0.7154	-0.4864	0.0840
Subsample 2: After the financial crisis									
W-L	-0.0299	-0.0112	-0.0067	-0.0063	-0.0050	-0.0031	-0.0026	-0.0024	-0.0016
t-stat.	1.4759	0.7791	0.8107	0.8364	0.7586	0.5148	0.4723	0.4594	0.3904
2-H	**2-1**	**2-2**	**2-4**	**2-8**	**2-12**	**2-16**	**2-20**	**2-26**	**2-52**
Full Sample									
W-L	-0.0114	-0.0033	-0.0067	-0.0073	-0.0051	-0.0035	-0.0034	-0.0022	-0.0005
t-stat.	-0.9554	-0.3888	-1.1953	-1.6003	-1.2853	-0.9717	-1.0128	-0.7065	-0.2174
Subsample 1: Before the financial crisis									
W-L	-0.0053	0.0004	-0.0067	-0.0070	-0.0045	-0.0030	-0.0033	-0.0013	0.0010
t-stat.	-0.3826	0.0446	-0.7818	-1.2519	-0.9253	-0.6612	-0.7755	-0.3324	0.3629
Subsample 2: After the financial crisis									
W-L	-0.0182	-0.0080	-0.0067	-0.0079	-0.0052	-0.0036	-0.0031	-0.0031	-0.0022
t-stat.	0.8855	0.5550	0.9026	1.0384	0.7780	0.5876	0.5454	0.5675	0.5263
4-H	**4-1**	**4-2**	**4-4**	**4-8**	**4-12**	**4-16**	**4-20**	**4-26**	**4-52**
Full Sample									
W-L	-0.0175	-0.0126	-0.0067	-0.0110	-0.0076	-0.0055	-0.0050	-0.0032	-0.0009
t-stat.	-1.4528	-1.4973	-2.4252**	-2.4008**	-1.9045*	-1.5415	-1.4973	-1.0103	-0.3775
Subsample 1: Before the financial crisis									
W-L	-0.0123	-0.0091	-0.0067	-0.0107	-0.0065	-0.0050	-0.0047	-0.0015	0.0015
t-stat.	-0.8791	-0.9080	-1.8083*	-1.9296*	-1.3330	-1.1069	-1.1076	-0.3875	0.5335
Subsample 2: After the financial crisis									
W-L	-0.0238	-0.0175	-0.0067	-0.0115	-0.0080	-0.0056	-0.0047	-0.0045	-0.0032
t-stat.	1.1411	1.2117	1.6857*	1.5096	1.1887	0.9026	0.8143	0.8277	0.7712
8-H	**8-1**	**8-2**	**8-4**	**8-8**	**8-12**	**8-16**	**8-20**	**8-26**	**8-52**
Full Sample									
W-L	-0.0221	-0.0174	-0.0067	-0.0109	-0.0073	-0.0060	-0.0048	-0.0031	-0.0009
t-stat.	-1.8270*	-2.0545**	-2.4767**	-2.3696**	-1.8270*	-1.6523*	-1.4062	-0.9766	-0.3606
Subsample 1: Before the financial crisis									
W-L	-0.0186	-0.0153	-0.0067	-0.0104	-0.0066	-0.0055	-0.0035	-0.0002	0.0028
t-stat.	-1.3251	-1.5192	-2.0066**	-1.8551*	-1.3156	-1.1962	-0.8005	-0.0484	0.9889
Subsample 2: After the financial crisis									
W-L	-0.0275	-0.0211	-0.0067	-0.0108	-0.0071	-0.0053	-0.0048	-0.0050	-0.0038
t-stat.	1.2951	1.4298	1.5442	1.4024	1.0354	0.8325	0.8209	0.9089	0.9431
12-H	**12-1**	**12-2**	**12-4**	**12-8**	**12-12**	**12-16**	**12-20**	**12-26**	**12-52**
Full Sample									
W-L	-0.020	-0.016	-0.007	-0.009	-0.007	-0.005	-0.004	-0.003	-0.001
t-stat.	-1.657*	-1.813*	-2.224**	-1.934*	-1.725*	-1.499	-1.202	-0.894	-0.362
Subsample 1: Before the financial crisis									
W-L	-0.017	-0.014	-0.007	-0.008	-0.006	-0.003	-0.001	0.001	0.004
t-stat.	-1.190	-1.317	-1.722*	-1.412	-1.147	-0.753	-0.233	0.365	1.354
Subsample 2: After the financial crisis									
W-L	-0.022	-0.018	-0.007	-0.008	-0.006	-0.005	-0.005	-0.005	-0.004
t-stat.	1.101	1.172	1.291	1.074	0.872	0.833	0.852	0.973	1.120
16-H	**16-1**	**16-2**	**16-4**	**16-8**	**16-12**	**16-16**	**16-20**	**16-26**	**16-52**
Full Sample									
W-L	-0.0172	-0.0130	-0.0067	-0.0086	-0.0063	-0.0046	-0.0036	-0.0021	-0.0008
t-stat.	-1.3981	-1.4901	-1.7953*	-1.8202*	-1.5357	-1.2279	-1.0524	-0.6566	-0.3289

Subsample 1: Before the financial crisis									
W-L	-0.0138	-0.0106	-0.0067	-0.0078	-0.0041	-0.0012	0.0007	0.0033	0.0048
t-stat.	-0.9479	-1.0113	-1.3436	-1.3270	-0.7891	-0.2460	0.1640	0.8404	1.6549*
Subsample 2: After the financial crisis									
W-L	-0.0193	-0.0143	-0.0067	-0.0075	-0.0060	-0.0053	-0.0055	-0.0055	-0.0046
t-stat.	0.8801	0.9319	1.0103	0.9400	0.8387	0.8094	0.9005	0.9519	1.2423
20-H	**20-1**	**20-2**	**20-4**	**20-8**	**20-12**	**20-16**	**20-20**	**20-26**	**20-52**
Full Sample									
W-L	-0.0168	-0.0136	-0.0067	-0.0083	-0.0057	-0.0043	-0.0032	-0.0016	-0.0010
t-stat.	-1.3615	-1.5526	-1.8866*	-1.7386*	-1.3813	-1.1639	-0.9173	-0.5025	-0.3759
Subsample 1: Before the financial crisis									
W-L	-0.0140	-0.0121	-0.0067	-0.0063	-0.0019	0.0005	0.0023	0.0051	0.0056
t-stat.	-0.9547	-1.1415	-1.4995	-1.0596	-0.3757	0.1016	0.5223	1.2765	1.9270*
Subsample 2: After the financial crisis									
W-L	-0.0191	-0.0142	-0.0067	-0.0085	-0.0070	-0.0067	-0.0065	-0.0069	-0.0056
t-stat.	0.8696	0.9276	1.0326	1.0505	0.9585	1.0029	1.0433	1.1640	1.5577
26-H	**26-1**	**26-2**	**26-4**	**26-8**	**26-12**	**26'-16**	**26-20**	**26-26**	**26-52**
Full Sample									
W-L	-0.0144	-0.0114	-0.0067	-0.0070	-0.0050	-0.0034	-0.0021	-0.0012	-0.0013
t-stat.	-1.1640	-1.2973	-1.5166	-1.4554	-1.1858	-0.8913	-0.6063	-0.3793	-0.4993
Subsample 1: Before the financial crisis									
W-L	-0.0091	-0.0064	-0.0067	-0.0015	0.0016	0.0039	0.0058	0.0073	0.0065
t-stat.	-0.6168	-0.5924	-0.6881	-0.2532	0.3039	0.7981	1.2651	1.8079*	2.1680**
Subsample 2: After the financial crisis									
W-L	-0.0185	-0.0154	-0.0067	-0.0111	-0.0096	-0.0090	-0.0090	-0.0094	-0.0072
t-stat.	0.8301	0.9986	1.1841	1.3465	1.3190	1.3111	1.4188	1.5932	2.2284**
52-H	**52-1**	**52-2**	**52-4**	**52-8**	**52-12**	**52-16**	**52-20**	**52-26**	**52-52**
Full Sample									
W-L	-0.0120	-0.0095	-0.0067	-0.0065	-0.0056	-0.0049	-0.0046	-0.0042	-0.0035
t-stat.	-0.9236	-1.0198	-1.2122	-1.2852	-1.2670	-1.2208	-1.2225	-1.2072	-1.2734
Subsample 1: Before the financial crisis									
W-L	0.0010	0.0033	-0.0067	0.0049	0.0060	0.0064	0.0066	0.0071	0.0061
t-stat.	0.0622	0.2754	0.3790	0.7441	1.0282	1.1949	1.3165	1.5838	1.8347*
Subsample 2: After the financial crisis									
W-L	-0.0216	-0.0193	-0.0067	-0.0148	-0.0137	-0.0124	-0.0119	-0.0118	-0.0074
t-stat.	1.0045	1.2774	1.5434	1.9564**	2.1246**	2.3137**	2.4408**	2.7317**	2.3622**

Note: all returns are normalized to one-month return for comparison purpose.

T-test is conducted for two sample (W and L) means with hypothesis that two means are equal.

**Significance at 5% level and lower

*Significance at 10% level

BI Norwegian Business School – Preliminary Thesis Report

Contrarian and Momentum Strategies -- Evidence in China Stock Market 2001-2011

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1. Introduction to Research Topic

The main objectives of the thesis can be summarized as below:

Firstly, we want to examine the profitability of various contrarian and momentum strategies in China stock market from 2002 to 2011. By doing so, we can see to what extent China stock market has changed and developed. Especially, this sample period includes the latest financial crises from 2007 to now. The investigation is expected to shed lights on investment strategies through market down turns.

Secondly, we aim to investigate alternative sources of the abnormal profits specific to China stock market. The assumed sources for examination are time-varying market risk, overreaction to firm-specific information, and lead-lag structure effect as documented by Kang et al. (2002). Besides, we want to investigate disposition effect in explaining these momentum profits.

Thirdly, if it is applicable, we would like to repeat the Jegadeesh and Titman (1995) one-factor model and decompose the relative importance of alternative sources. By comparing the results with Kang et al. (2002), we might generate a new view on the China stock market. We hope to internalize latest finding regarding the topic and provide evidence for both investors and financial researchers.

In accordance of the efficient market hypothesis, as refined by Eugene Fama (1970), security prices, at any time, fully reflect all available information in an efficient market. Price changes only to reflect new information. As new information is unpredictable, price changes should be unpredictable. Thus, price is following a random walk and no investment pattern can be discovered for the purpose to capture excess return. It results that no investors can outprofit the others by predicting the stock returns. Among the three versions of EMH, the weak-form hypothesis suggests that all historical prices and returns have been reflected on current prices. Thus no technical analysis can predict or help to form strategies to beat the market. However, empirical tests using serial correlation on stock returns find out stock market returns have a tendency to be related to past stock returns， which contradicts to the weak-form EMH. Considerable quantities of financial literatures, since 1980s, have shown that historical stock returns have predictability for future stock returns in different time horizons, challenging the weak-form EMH in the tested markets. For instance, Lo and Mackinlay (1988) report weak positive serial correlation on short horizon (1-6 months) by examining the US market index, that positive past return leads to positive current return. And for individual securities, reversal effect seems more common as indicated by Lehmann (1990) and Jagedeesh (1990), that US stock with positive past return tend to reverse and perform poorly later on. Moreover, portfolio of US stocks experiences continuation (momentum) effects on intermediate horizon (3-12 months) as documented by Jagedeesh and Titman (1993) that past winner (loser) portfolios perform continuously over time. On the other hand, Debondt and Thaler (1985, 1987) find out that in US market reversal (contrarian) effect happens on long horizon (3-5 years) that recent loser portfolios currently outperform recent winners.

With the suggestion of momentum effect and reversal effect along the time horizon on cross-sectional stock returns, abnormal profits can be obtained by forming the portfolio-investment strategies: momentum strategies and contrarian strategies. Momentum (strengthen) strategy is to buy the past portfolios that performed well and sell the past portfolios that performed poorly (buy past winner and sell past loser), because prior winner is likely to become current winner. While contrarian strategy is to do the opposite in the belief of prior winner will become current loser.

Momentum and contrarian strategies have been first tested and documented profitable to some extent in the US market as shown above. Recently, Parhizgari and Nguyen (2008) come up with considerable support for the presence of the momentum and contrarian strategies in the American Depositary Receipts (ADRs) market. Besides, the momentum or contrarian effects are found in non-US markets as well. Ahmet and Nusret (1999) discover long-term contrarian effects in the stock markets of seven non-US industrialized countries. Rouwenhorst (1998) reports momentum profits in 12 European equity markets. Schiereck et al. (1999) find momentum profits in the intermediate-term, and short- and long-term contrarian profits in the Germany equity market. Chang et al. (1995) reports short-term contrarian effects in the Japan stock market. Not only in developed countries, but also the emerging markets experience the momentum or contrarian effects to different degree. Rouwenhorst (1999) discovers momentum profits in six out of twenty emerging equity markets. Hameed and Ting (2000) also document short-term contrarian strategies results in abnormal profits in the Malaysia stock market. Locke and Gupta (2009) report contrarian strategies profitable in the Indian market.

Specifically for China market (including Hong Kong), a few valuable literatures regarding the discovery of momentum or contrarian effects have captured researcher's interest. Existing findings are, for example, that Ding et al. (2008) document momentum and contrarian profits in seven Pacific-Basin markets including China. They also report that this effect especially pronounced in Hong Kong. Hameed and Yuanto (2000) find small momentum profits in six Asian stock markets and China is one of them. Kang et al. (2002) document significant profits on short-term contrarian effect and intermediate-term momentum effect in China for the period 1993 to 2000. By investigating only Shanghai stock exchange, Naughton (2008) suggests substantial profitability on momentum strategies during 1995 to 2005. On the other hand, Li et al (2010) suggest no momentum profitability for the period 1994 to 2007 while support that the short-term contrarian strategies can capture, on average, 12% abnormal return annually. Du and Nie (2007) find evidence supporting no intermediate-term momentum effect, but profitable long-term (18-36 months) contrarian effect.

Why momentum strategies or contrarian strategies can beat the market as the empirical studies shown? Former researchers try to figure out explanations to momentum and contrarian profits, which basically related to behavioral irrationality and stock market inefficiency.

Among the alternative sources for the abnormal return brought along by contrarian strategies, investor's overreaction to information is the most notable one. As DeBondt and Thaler (1985) illustrate, overreaction hypothesis suggests that extreme price movement leads to an opposite-direction price movement later, which matches the magnitude of the initial price movement. The overreaction hypothesis is tested predictive as on long-term contrarian profitability in the US market. It is iterated that investors tend to overact with bad, firm-specific news. The pessimistic attitude drags down the price. As what goes down must come up, the negative serial dependence of individual security raises possibility for past loser to outperform the past winner. And contrarian strategy exploits this phenomenon. The hypothesis is supported by Lehmann (1988), Delong et al. (1989) and so on. Later, short-term contrarian effect is also explained by overreaction as Bacmann and Dubois (1998) test it on the French market, which is supported by Mun et al. (1999) investigating the French and German market.

Another possible explanation for contrarian effect is documented as "size-dependent lead-lag structure" or "cross effects among the securities" by Lo and Mackinlay (1990). They suggest that some stocks react more quickly than the others, resulting in "return of large stock generally leads those of smaller ones", which explains more than 50% of abnormal return gained by the contrarian investment rule. Given the fact that individual security return is negatively autocorrelated while the market index is positively autocorrelated, if some stock (A) obtained higher return previously cross-autocorrelated with some other stock (B), the contrarian strategy (buy loser and sell winner) benefits with no existence of market overreaction. However, their suggestion is refuted by Jegadeesh and Titman (1995). They discompose the contrarian profits and find out that stock price delay reacts to common factors and overreact to firm-specific information. The size-related lead-lag effect arises only when investor delay reactions to common factors. They conclude that overreaction to firm-specific information is the main contribution to contrarian profits.

A Third source of contrarian profits can be time-varying common factors. As was highlighted in the research conducted by Conrad and Kaul (1998), cross-sectional dispersion in the mean return of individual securities (which consisting in the portfolio traded) varying by time is the important determinant for short-term contrarian profits. In determining the long-term contrarian profits, Chan (1988) suggests that both the risk of individual stock (represented by beta) and the market risk premium change along time, which give rises to reverting mean of expected return. And prior loser have higher risk later implying higher expected return, from which contrarian strategies benefit. Zarowin (1990) reports firm-size discrepancy is the main reason for long-term contrarian profits. It is documented that prior loser can outperform winner because it is of smaller size but not overreaction. Some other reasons lay on measurement error due to bid-ask spread, nonsynchronous trading and liquidity as reported by Park (1995), Ball et al. (1995), Conrad et al. (1997).

Similarly, interpretations of momentum profits are widely debated. Among those the main idea is either behavioral bias that investors irrationally react to information and tend to act in a "herd-like manner" when information is released;

or data snooping bias. Behavioral theory related to cognitive bias have been attempted by Barberis et al. (1998) and Dan- iel et al. (1998). To achieve the same goal, Hong and Stein (1997) focus on Asian market and categorize investors into "newswatchers" and "momentum traders". In their theory, newswatchers underreact to information in short run, which is being taken advantage by momentum traders to drive up the price and earn substantial return. In the long run, price is overshoot and beyond the equilibrium value. It is the interaction between traders causes the short-term momentum profits. Among those herding effect is well documented. For example, by investigating the institutional investors (mutual funds) in the US market, Grinblatt et al. (1995) suggests that herding behavior significantly related to the performance of the funds. Funds tend to invest in portfolio of stocks based on the their past result. As De Long et al. (1990) points out, funds are "positive-feedback traders" who invest in stocks have performed well. In Grinblatt's paper, they also find that funds tend to trade simultaneously with same direction, which pushes up the prices. This result explains intermediate-term momentum strategies.

As newly developed a behavioral bias, disposition effect as termed by Shefrin and Statman (1985), is found explanatory to momentum strategy in Grinblatt and Han (2005). Disposition is described as investors tend to sell winners too quickly and keep losers too long. And if to some extent disposition effect exists with investors, stocks with aggregate unrealized capital gains tend to outperform stocks with aggregate unrealized capital losses. Enhance, disposition effect may account for momentum profits. Hur et al. (2010) point out that disposition effect seems to be stronger within individual investors dominant market.

Moreover, to interpret the intermediate-term momentum profits, another source is belonging to market inefficiency due to time-varying common factors or data mining. Jegadeesh and Titman (1993) report that higher-risk stocks are contained in prior winner results in which higher expected return in the intermediate term. Enhance, the profits are compensation to the risk. While Conrad and Kaul (1998) suggest cross-sectional differences in mean returns give rises to intermediate momentum profits. However, their suggestion is refuted by Jegadeesh and Titman (2000), which eventually confirms the delayed overreaction theory. After that, Choria and Shivakumar (2000) control the momentum strategies by lagged macroeconomic variables and find that payoffs disappear. They conclude that time-varying expected return is the main reason for momentum profits.

2. Research Questions and Objectives

In this thesis, we aim to investigate various contrarian strategies and momentum strategies in China market for basically four motivations. First of all, the main land China (excludes Hong Kong, Macau and Taiwan)，with population of 13.4 billion[9], ranks the second largest economies in the world (ahead of Japan which GDP is $5.50 million and after the U.S.) with GDP $5.88 million[10] in 2010. GDP growth rate is 10.3%, listing the 6th place in the world behind Taiwan (10.8%) and India (10.4%)[11]. Total trade becomes $2.97 billion[12], making China the second trade union in the world after the U.S. The importance of China market to the global economy is recognized and much accounted. Researches in China stock market may give rises to understand the development of global economy. As the most important emerging market, China is in need of more investigation from year to year as it is developing so fast. Despite prior Chinese-market studies discussed previously in the paper, a stylized explanation of contrarian and momentum profits is waiting to be developed.

What's more, even though China has been a member of WTO since 11 December 2001, the integration of China stock market and the global market remains weak. Byströma (2011)[13] reports that China's stock market has much weaker reaction to the global news. Sharma (2011)[14] examines the Asian economies and documented China is the least positively related to the US market. Although China market is no longer negatively related to the U.S. market as

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[9] National Bureau of Statistics of China, the 6th national census of population results, 28 April 2011

[10] World Development Indicators database, World Bank, 1 July 2011

[11] GDP (real) growth rate list by the CIA World Factbook

[12] PRC National Bureau of Statistics， 2010 year report, 28 February 2011

[13] Byström, Hans. Does the Chinese stock market react to global news? Journal of the Asia Pacific Economy Vol. 16, Iss. 3, 2011

[14] Sharma, Preeti . Asian Emerging Economies and United States of America: Do they offer a diversification? Australian Journal of Business and Management Research. Vol.1, Iss.4, (85-92) 2011

indicated in Kang et al. (2002), if China market is not perfectly correlated to the U.S. securities, it will provides diversification benefits for international investors. Hence, the investigation of proper investment strategy in China stock market is still attractive and interesting to the global investors and researchers.

In addition, China stock market is a special market. In its first ten years, it was interpreted as “stir-frying stocks” for stock trading in China. Kang et al. (2002) and Hu (1999) point out that individual investors, which have unique practice, dominate China stock market. And the characteristics of the market can be summarized as: 1. Poor regulation and little reliable public information; 2. Few products and little variety for choosing. Individual investors lacking of trading experience and solid knowledge about capital market tend to believe in rumors around the market. Such a different behavior leading to overreaction to the news followed by a quick correction seems to contribute most for the short-term contrarian. What’s more, investors experience herding effect, which makes persistent stock return causing possible momentum effect. Kang et al. (2002) also suggest that syndicate speculators are much easier to manipulate the sentiment in small stocks, giving rises for return of small firms lead returns of large firms. As shown in the SZSE Fact Book 2009, individual investors are still the dominance of China stock market despite that the percentage of institutional investors is increasing throughout the years. We have confidence that the unique practice remains unchanged but any difference due to market development is an interesting question.

Last but not the least, the past 10 years is the second decade of China stock market since the establishment of two stock exchanges in 1990 and 1991. Since 2001, much changes and development is observed in the China stock market. Government regulations are gradually standardized and improved. For example, Shenzhen, Shanghai Stock Exchange IPO regulation is exercised in 8th June 2001. Also, in the same year, Shenzhen, Shanghai Stock Exchange Trading Rules is exercised. In 2004, multi-layer capital market system was developed with the establishment of middle and small firm market sector in Shenzhen Stock Exchange. Moreover, product variety is increased. B shares are opened for domestic investors, which are limited to foreign investors only prior 2001. The first open-end fund was traded in 2001. Also, index futures were established for trading and short selling is allowed for it in 2010. With these changes, we cannot deny that the China stock market is getting more and more regulated, transparent and mature. As Kang et al. (2002) says, “the profitability of contrarian strategies (and, to a less extent, momentum strategies) will dissipate as the market becomes mature and more transparent in the future,” we are expecting to see different results in this investigation.

The rest of this preliminary thesis report is organized as: we discuss the data collection plan and sample selection. Then methodologies regarding identification of abnormal profits as well as the examination of alternative sources are presented. Finally, it is our plan for thesis progression.

3. Plan for Data Collection

3.1 The data for conducting the research of momentum/contrarian effects

Following the methodology described by Jegadeesh and Titman (1993) and Kang et al (2002), the weekly stock return of both “A” shares (satisfied requirements below) from December 2001 to November 2011 are to be retrieved from DataStream. We will start from Monday, December 3, 2001 and ends at Monday, November 28, 2011. In order to implement intermediate-term and long-term momentum strategies, our sample is going to exclude the firms that were delisted during the sample period, and include in it only the firms that have been trading since December 3, 2001. So all the firms included must have continuous trading throughout the sample period, namely ten years (i.e. any firm with missing data for any reason would be excluded). We are also going to exclude the IPOs that were listed on December 3, 2001, since the first trading days for IPOs are normally so volatile that it may distort the findings in our short term momentum and contrarian strategies. There were 1160 firms that were listed in the China stock market (both Shanghai and Shenzhen Stock Exchanges) and hopefully we will still have a sample size large enough for research purpose after all the requirements.

However, there is possibility that we may end up with a sample size not sufficient for our studies. There is a backup plan: the sample is going to include the firms that had been listed for at least 5 years prior to November 2011 and exclude those listed in or after 2006. According to the statistics from the China Securities Regulatory Commission, the numbers of firms listed in both Shanghai and Shenzhen Stock Exchanges since 2005 is 1381. Therefore even taking into consideration of the firms that are delisted, we still have a sample size large enough for our research. However, in this case, the first week return of any newly listed company is eliminated because of the substantial underpricing and irregular returns in IPOs in China (see Sun and Tong, 2000), so that to make the result more reliable.

In order to test for the financial crises period, whether any specific strategy may capture abnormal return, we plan to use subsamples: December 2001 to November 2006, and December 2006 to November 2011. The comparison between subsamples and entire sample may generate interesting results.

3.2 Possible additional data needed for explaining the momentum/contrarian effects

According to Kang et al (2002), the contrarian and momentum profits in China could be linked to four factors: (1) measurement error; (2) time-varying market risk; (2) overreaction to firm-specific information and (4) lead-lag structure in stock returns. To investigate whether the four points raised by Kang et al (2002) still have explanatory power for our sample period, we determine that we need the following additional data:

- Weekly market return from December 2001 to November 2011: proxy by Shanghai "A" share Index[15] and Shenzhen "A" share Index[16], depending on which market is the stock listed on，can be obtained from DataStream.
- Weekly risk-free rate: from December 2001 to 7th October 2006, it represented by China one-year deposit rates that are accessible through The People's Bank of China.[17] Since 8th October 2006, Shanghai Interbank Offered Rate (Shibor)[18] is used

[15] Shanghai "A" share Index was formed by Shanghai Stock Exchange with sample of all the "A" shares listed. The base year is 1990. It was first published in Febuary,1992.

[16] Shenzhen "A" share Index was formed by Shenzhen Stock Exchange with sample of all the "A" shares listed. The base year is 1991. It was first published in October,1992.

[17] The People's Bank of China. http://www.pbc.gov.cn/

[18] Shibor is calculated, announced and named on the technological platform of the National Interbank Funding Center in Shanghai. It's shared information with 16 commercial banks in China since October 2006. http://www.shibor.org/shibor/web/html/index_e.html

instead[19] until the end of our sample period. Shibor data can be collected on its website.

- Market value/capitalization figure of each listed company during the sample period: data can be collected from DataStream as the fundamental information.

4. Methodology

4.1 Test of momentum and contrarian profits

To test the existence of momentum and contrarian profits. Portfolios are formed based on the methodology employed in Lo and MacKinlay (1990), Jegadeesh and Titman (1995), and Kang et. al (2002). We first rank the stock returns during the F-week portfolio formation period in an ascending order. We plan to examine 10 formation periods, thus F=1, 2, 4, 8, 12, 16, 20, 26, 52. Five equal-size quintiles are then formed. The portfolio with the highest equal-weighted average stock returns is the winner portfolio and the lowest is then the loser portfolio. The quintiles in between the loser and winner portfolios are given number orders in ascending order (2, 3, 4). Second, each quintile portfolio under various formation periods is also held for a H-week holding period. We consider using the same horizons in the formation period as in the holding period, thus H=1, 2, 4, 8, 12, 16, 20, 26, 52. By then, a F-H strategy is formed. As we each have 9 time horizons for both formation (F) and holding (H) periods, we are going to have 81 (9x9) different investment strategies. Lastly, an equal-weighted average portfolio return for holding period is calculated for each F-H strategy. The quintile with the highest return in each strategy is selected as the winner portfolio currently whereas the lowest one is named the loser portfolio currently. The difference between the returns of winner and the loser portfolio (L - W) is calculated and reported. If the difference is significantly different from zero and it is positive, we can conclude that momentum profits exist. And if it is significantly negative, then contrarian strategy is profitable. Similarly, value-weighted average portfolio return is also calculated for comparison purpose and check our whether firm-size effect was considerable.

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[19] The change of the data target as the risk-free rate may raise inconsistency problem. However, since one-year deposit rate changes as the PBC announces a new rate at certain date in a year, it remains constant otherwise. We find Shibor more consist with the economic fluctuation from time to time even though it was newly developed.

To make it clearer, here is an example. If F=1 and H=1, we will start from the first week of our sample and find out winner and loser portfolio by sorting stock returns as described above. Then the returns of these portfolios for the next week (holding period is one week) are calculated. Then this process is carried over starting with the second week of our sample until the last but second week of our sample. By repeating the process continuously, a number of current winner returns and loser returns will be generated. Then we take average of them. By comparing average winner and loser returns, we can conclude whether this F,H (1,1) strategy generate momentum or contrarian profits. If then for F=1, and H=4, we also start from the first week. But the holding period will be from the second week to the fifth week, totally four weeks. The process as discussed above is carried over a long time. While F=4, and H=1 implies formation period is the first four weeks and followed by one week holding period.

To avoid the possible measurement error that may arise from bid-ask spread, price pressure due to illiquid markets, and non-synchronous data, one trading day between portfolio formation and holding periods for all investment strategies will be skipped (Kang et al., 2002; for similar treatment, see Chan et al., 1999; Lehmann, 1990). For instance in the formation period, a week may beings on Tuesday and ends on the following Wednesday (if the Wednesday is not a trading day, then the next trading date is used). Then for the holding period, a week begins on Wednesday and ends on Thursday (if Wednesday is not a trading day, then we will use the next trading day). To be more robust, we might try skipping one week in between as well.

4.2 Examine the effect of time-varying market risk to abnormal profits

Once we find out what time horizon strategies can generate abnormal profits, we will focus on these strategies and test for each alternatives sources as discussed in the objectives in session 2.

Chan (1988) proposes that the common factors for winner and loser stocks are not constant over time. He finds that only small abnormal profits exist for contrarian strategies as losers tend to be riskier and winners tend to be less risky in the holding periods. He also proposes the following model to investigate whether time-varying market risk plays a significant role in explaining the contrarian and momentum profits:

$$r_{pt} - r_{ft} = \alpha + \beta\left(r_{Mt} - r_{ft}\right) + \varepsilon_t,\ P \in \left(W, L\right) \quad (1)$$

$$r_{LT} - r_{WT} = \alpha^c + \beta^c\left(r_{MT} - r_{fT}\right) + \varepsilon_T, \qquad (2)$$

$$r_{WT} - r_{LT} = \alpha^m + \beta^m\left(r_{MT} - r_{fT}\right) + \varepsilon_t \qquad (3)$$

Where r_{pt} is the portfolio return at time t (t is those time in formation period), r_{ft} is the risk-free rate at time t, r_{Mt} is the market index return at time t, r_{Mt} - r_{ft} is the market risk premium at time t, α and β are the intercept and slope (market beta) coefficients, r_{LT} is loser's return at time T (T is those time in holding period), r_{WT} is winner's return at time T. The superscripts c and m refer to contrarian and momentum strategies, respectively. If the betas are significantly different for winner portfolio and loser portfolio in all the strategies, then beta risk contributes to abnormal returns in these strategies. Kang et at (2002) follows model (Chan, 1988) to investigate whether the time-varying risk plays an important role in the momentum/contrarian effect in the China stock market from 1993 to 2000. Their results lead to the conclusion that the beta risk alone cannot explain the contrarian and momentum profits they found in the same period.

4.3 Examine the effect of overreaction and lead-lag structure to abnormal profits

Based on the idea illustrated by DeBondt and Thaler (1985), overreaction effect causes negative serial autocorrelation of individual security. To test whether overreaction effect has influence the abnormal return, we tend to follow the method used by Kang et al. (2002). For each strategy tested to be profitable, we will construct 5 size-sorted quintile portfolios of stocks based on stock's capitalization at initial portfolio formation time. The quintiles are presented as S1 (the smallest stocks) to S5 (the largest stocks). For example, if F-H (1,1) contrarian strategy is tested profitable, then under this strategy, stocks under each quintile will go through the process as firstly to be defined as winner or loser in the formation period; secondly to be held for the holding period and see how much profits (returns) can be obtain by contrarian strategy. Such returns construct a serial under each quintile over time. Then correlation between each quintile return and its own one-week lagged return (own-serial autocorrelation) as well as the one-week lagged return of other four quintiles respectively (cross-serial autocorrelation) was calculated. Later, a 5×5 correlation matrix is formed. If negative own-serial autocorrelation is dominant, then it indicates an overreaction to firm-specific news. And if the result is positive, then we can conclude a witness of delayed reaction.

Moreover, by checking the cross-serial autocorrelation, we can see whether smaller stock's return is leading the larger stock's return. If it is significantly positive, for example, the correlation of S1 to lagged S5, then we can confirm the previous hypothesis.

4.4 Decomposition by one-factor model

Lo and Mackinlay (1990) propose that the lead-lag structure is an important source contrarian profits, whereas Jegadeesh and Timan (1995) find no evidence for lead-lag structure in the U.S. market. J. Kang et al. (2002) indicates that the lead-lag structure in China may be an important source of momentum profits, but not of contrarian profits. We will follow the method developed by Lo and MacKinlay (1990) and Jegadeesh and Timan (1995) to decompose the profit sources for contrarian and momentum strategies. Firstly, a one-factor lagged model is used to describe individual stock i's return:

$$r_{i,t} = \mu_i + b_{0,i}^t f_t + b_{1,i}^t f_{t-1} + e_{i,t} \qquad (4)$$

Where μ_i is the unconditional expected return of stock portfolio i, f_t is the unexpected common factor at time t. In the context of Kang et al (2002), the market index return obtained from Eq. (1) is used as a proxy for the common factor. We plan to follow Kang et al (2002) if we find momentum/contrarian effects in the China stock market for the period we investigate but we will use the market index as described in data session. $b_{0,i}^t$ and $b_{1,i}^t$ are *i*th stock's current and lagged betas, respectively. The assumption is that if the one-factor model with one-period lag can explain the stock return and if the past market return can will explain a portion of the excess return of the stock, then the expected contrarian and momentum profits can be decomposed as follows (Lo and MacKinlay, 1990):

$$E(\pi^c) = -E\left(\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{m,t-1})r_{i,t}\right) = -\sigma_u^2 - \Omega - \delta\sigma_f^2 \qquad (5)$$

$$E(\pi^m) = E\left(\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{m,t-1})r_{i,t}\right) = \sigma_u^2 + \Omega + \delta\sigma_f^2 \qquad (6)$$

Where

$$\sigma_u^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \mu_m)^2 \tag{7}$$

$$\Omega = \frac{1}{N}\sum_{i=1}^{N}\text{cov}(e_{i,t}, e_{1,t-1}) \tag{8}$$

$$\delta = \frac{1}{N}\sum_{i=1}^{N}(b_{0,i} - \bar{b}_0)(b_{1,i} - \bar{b}_1), \ \ \delta = E(\delta) \tag{9}$$

According to Eq. (5) and Eq. (6), there are three components for the expected contrarian profits and momentum profits. The first (σ_u^2) is the cross-sectional variance of expected returns. For contrarian strategies (Eq. 5), higher average return hurt the contrarian profits while the same component increases momentum profits. The second component Ω is the cross-sectional average serial covariance of idiosyncratic component of individual stock returns. The component represents the magnitude of overreaction to firm specific information. The last component $\delta\sigma_f^2$ is the lead-lag structure. If $\delta<0$, then the lead-lag structure has a positive effect on contrarian profits and negative effect on momentum profits, or vice-versa. We will report all of the three (δ_u^2, Ω and δ) for all our quintile portfolios and thus the magnitude of the overreaction effect as well as the size-related lead-lag structure can also be quantified and compared.

5. Proposed Thesis progression

Our plan is to divide our research into 4 parts in this year:

1) First part is the data collection. We plan to finish all the data collection by February 29, 2012.
2) We will start to form portfolios and construct momentum and contrarian portfolios in the second part. The results will be reported by April 30, 2012. A basic write-up about this part will also be finished by the same day.
3) In the third phase we are going to finish exploring the results from our findings in the momentum and contrarian portfolios (i.e. examination of alternative explanatory sources and decomposition return) by June 30, 2012.
4) In the last part we are going to finish all the write-up by July 31, 2012 and any grammar mistakes or minor mistakes need to be checked in the rest one month.

The purpose of having the thesis divided into parts and deadlines is to monitor the progress of the thesis and make sure we can consult and report to our supervisors.

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