Noise or Reality: An Empirical Study of Target Pre-bid Returns

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ABSTRACT

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Providing new evidence derived from a large sample simulation using US exchange-listed firms from 1990 to 2012, this paper contributes to the discussion about 1) the magnitude of target pre-bid abnormal returns (conventionally called the "run-ups") and 2) the substitution and mark-up pricing relation between pre-bid run-ups and post-bid mark-ups of M&A targets. As random simulation represents the normal scenario (i.e. probability of M&A announcement is unpredictable), we should consider empirically derived critical values of simulation run-ups as the new benchmarks when testing the significance of the target's pre-bid abnormal return. The fact that only 13% of M&A run-ups could be recognized as abnormal when compared to new benchmarks raises doubts about the traditional approach. In the examination of the relationship between run-ups and mark-ups, a 0.4674 coefficient in the regression of mark-up on run-up using pure random sample makes significant contribution to the debate upon substitution and mark-up pricing hypotheses. If we take 0.4674 as a baseline, the coefficient of the regression is supposed to be smaller if substitution hypothesis outweighs mark-up pricing hypothesis, otherwise this coefficient will be larger than 0.4674. Although the conclusion is still open, findings in this paper and in Schwert (1996) actually tend to support the substitution hypothesis instead of mark-up pricing hypothesis, suggesting pre-bid run-ups do not necessarily cause a higher bidding price for the bidders.

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1. Introduction

In the pre-bid stage, it is quite common for the bidding firms to experience great exposures to target stock price volatility. Since evaluation process for the target firm still goes on, the offer price is very sensitive to abnormal movements of target stock price during this stage. Thus, it is not surprising that target pre-bid abnormal returns have caused a widely discussion in the literature.

Schwert (1996) suggests a scenario which has been played out frequently in real life – the target stock price soars (the run-ups) before the bidding firm announce its offer, and thus the bidding firm faces a difficult situation where it has to decide whether to go ahead with its planned offer (ignore the run-ups), or to revise its bidding price by taking into account the increase of target stock price (which might indicate an increase of target's stand-alone value, and/or a potential contesting bidder). That being said, after examination using empirical data of exchange-listed targets from 1975 to 1991, pre-bid run-up of 13.3% and post-bid mark-up of 10.1% were reported in his study. Moreover, it has been documented that, comparing with a single bidder scenario, an auction is associated with an added takeover premium of 11.4% (Comment & Schwert, 1995), or even as high as 13% (Bradley, Desai, & Han Kim, 1988). In the latter case, pre-bid run-ups play an extremely important role in the construction of bidding cost.

To further examine the empirical relation between pre-bid run-ups and post-bid mark-ups, this paper uses a large random simulation sample as the comparison group, representing the "norm" of this real universe. It sets up an unconditional scenario that 1) helps us understand better how big the pre-bid run-up is and 2) contributes to the interpretation of relation between run-ups and mark-ups.

The structure of this paper is as follows: Section 2 reviews the related literature and the two competing hypotheses. Section 3 describes the data selection process, simulation construction process, and event study method applied in this paper. In Section 4, the event study results of the simulation samples are discussed. Analysis of the regression tests with related to pre-bid run-ups and post-bid mark-ups can be found in Section 5, and in Section 6 robustness tests have been conducted for the regression analysis. Section 7 concludes the findings of this paper.

2. Literature Review

2.1. Target Pre-bid Run-ups

To clearly define the two periods of interest, I follow previous studies and use pre-bid run-ups to represent the target abnormal return before first bid announcement. During this period, the market does not generally have information about potential bidder (s), and it is likely that the bidder knows very little with their rivals as well. After the first bid announcement occurs, the target and the bidder are in a public negotiation game where a rival bidder may emerge, leading to a higher premium paid by the winning bidder. Abnormal returns to target during the period from first bid announcement to the final outcome of the deal are denoted as the mark-ups.

Early studies of M&A cases before 1980 observed positive pre-announcement effects (Asquith, 1983; Dodd, 1980; Eckbo, 1983) with researchers observing an approximate 30% abnormal return to the target of tender offers over a period of one month, on average, before and after the announcement day (Bradley, Desai, & Kim, 1983; Bradley, 1980; Jarrell & Bradley, 1980). Later, Jarrell & Poulsen (Jarrell & Poulsen, 1989) found target shareholders in 526 bids from 1963-1986 received an average premium of 28.99% (CAR) over a period of [-20, +10].

Recent studies also recorded significant target pre-bid run-ups (Borges & Gairifo, 2013); King, 2009; Betton, Eckbo, & Thorburn, 2008; Schwert, 1996), and discussed questions about how big the pre-bid run-ups are, what causes the run-ups, and how do they affect the control premium paid by bidding firms. Following their discussion, this paper focuses on the last question and further contributes to the existing literature by using a comparison group constructed by large sample random simulations to evaluate the unconditional relationship between run-ups and mark-ups.

2.2. Substitution and Markup Pricing Hypotheses

Among the extensive discussions on bidders paying large premiums to acquire control of exchange-listed firms, it is conventionally considered that the premium consists of the abnormal returns earned by target shareholders, including a period of pre-bid run-up and a period of post-bid mark-up of target stock price.

Following Schwert (Schwert, 1996), a simple formula can be used to demonstrate the relation between run-ups and mark-ups: $Premium = Runup + Markup$.

Under the semi-strong form efficient market hypothesis (EMH) (FAMA, 1970), the market price reflects all public information. Provided that the target stock price rises on the announcement day, drops if the bid is not successful, and the outcome of a deal cannot be predicted (without private information), it is not possible to profit by buying target stocks on the offer announcement day (Bradley et al., 1983). In this case, most market investors are unable to earn significant abnormal returns without access to private information. Therefore, according to this theory, pre-bid run-ups and post-bid mark-ups should be uncorrelated under a normal scenario where there is no insider trading (they are merely "random walk" of target stock price) since price movement is unpredictable.

Not surprisingly, during a two-party negotiation, both bidder and the target usually have more private information than the market does due to information asymmetry and delayed price discovery process. They will choose to ignore the price run-ups if they are sure that the run-ups are caused by the leakage of their private information (i.e. insider trading) and thus the market price cannot reveal any new information to them. It is possible that post-bid mark-up decreases just after the pre-bid run-up goes up, as Schwert (1996) puts it, "each dollar of pre-bid run-ups offsets the post-bid mark-up one for one", and this theory is denoted as Substitution Hypothesis.

However, in most cases, both bidder and target are not sure whether run-ups also represent new private information held by other traders, or potential bidders (i.e. potential bidders may purchase target stock in the market). Thus it is consistent with the rational behavior of both bidder and target that they should update their evaluations for the target. The fact that bid premiums in M&A auctions are higher than those paid cases involving only one bidder provides support for this Markup Pricing Hypothesis:

the final deal price increases due to pre-bid run-ups, and each dollar of pre-bid run-up is added to the final deal price one-for-one if the mark-up is unaffected (Schwert, 1996).

3. Methodology

In order to make my study comparable with previous studies, I follow most of the sample firm selection requirements in Schwert (1996) and Betton et al. (2008) for choosing US M&A target sample; data in the simulation samples should meet the same criteria as those in M&A sample where the criteria are applicable.

3.1. Sample Data Selection

The initial M&A sample contains all the US targets traded on NYSE, AMEX, or NASDAQ in the bids collected by Thomson Reuters SDC Platinum if 1) the bid is with a deal type "merger" or "acquisition of majority interest" (transaction form "M" and "AM"), 2) the buyer owns at least 50% of the target equity after the deal, 3) disclosed value merger & acquisitions, 4) over the period of Jan 1st 1990 to Dec 31st 2012. An initial sample of 7,745 deals has been obtained.

As to simulation samples, I first choose all the US domestic companies listed on NYSE, AMEX, or NASDAQ between Jan 1st 1990 to Dec 31st 2012 as the original company sample, resulting in 20,342 companies in total. For each company, I pair it with each calendar day (denoted as the "pseudo" event day in this paper) from Jan 1st 1990 to Dec 31st 2012, which includes 8,401 calendar days in total. After combining each company with each calendar day, we get a simulation pool with full combinations of all the companies and dates.

Moreover, all the companies in the M&A sample and the simulation pool are also required to satisfy the following criteria:

(1) A stock price exceeding $1 over day-42 to day -1

(2) A total market equity capitalization exceeding $10 million on day -42

(3) Have at least 100 days of common stock return data in CRSP over the estimation period [-297, -43]

The sample cleaning process and observations included in the study at each are summarised Table 1. To clean the simulation pool, I first drop those combinations whose pseudo event day is not between the listing and delisting day of the firm (in other words, the stock does not trade on the stock exchange on that day), resulting in 62,121,172 combinations retained in the pool. After screening it using Condition (1) and (2) listed above, the final simulation pool includes 50,366,878 firm-date observations.

Table 1. Sample Cleaning Process and Sample Size

Simulation Pool	**N**
Initial Pool of Firm and Date Combination	170,893,142
Event Date Matches Listing Day	62,121,172
A stock price exceeding $1	53,397,611
A total market equity capitalization exceeding $10 million on day -42	50,366,878
Have at least 100 days of common stock return data in CRSP over the estimation period (day -297 to day -43)	46,718,352
Final Pool Size	*46,718,352*
M&A Sample	**N**
Initial M&A Pool	7,745
CUISIP Transfer to PERMNO on CRSP	6,733
A stock price exceeding $1	5,805
A total market equity capitalization exceeding $10 million on day -42	4,367
Have at least 100 days of common stock return data in CRSP over the estimation period (day -297 to day -43)	4,171
Final Sample Size	***4,171***

3.2. Simulation Construction

As mentioned in the previous section, the simulation pool is composed of all the possible combinations of firms and calendar days from 1990 – 2012, and, for each combination, the pseudo event day should be within the listing day and delisting day of a firm on its stock exchange. For example, the combination with a pseudo event day that lies before the IPO day (or after the delisting day) of the firm will be excluded.

The rationale behind this methodology is similar with the simulation construction method used by (Kothari & Warner, 1997) in their study on long-horizon security price performance.

With the cleaned pool, a cross-sectional daily event study has been conducted for each combination in the pool over a pre-bid event window of [-42,-1] and a post-bid event window of [0, +126 or delisting day], which results in 46,718,352 CAR run-ups and mark-ups pairs (combinations that do not satisfy Condition (3) listed above have been excluded from the sample). The simulation samples are then generated from this pool of firm and date combinations using both simple random selection and time stratified selection methods.

The advantages of this sample construction method is that the pool is representative of the unconditional population which contains all the takeover targets and non-takeover firms. By investigating the stock response to pseudo announcements, or "events", we observe the unconditional level of "abnormal returns" to these firms.

When compared to the pre-bid run-ups of the M&A sample, the simulation sample suffers less in terms of time contamination, or overlapping of event windows, while conducting regression analysis.

3.2.1. Simple Random Selection Method

Simple random selection method simply selects n firm-date combinations from the simulation pool (n equals the size of M&A sample, here $n = 4171$) without any other considerations. Each combination has an equal opportunity to be chosen for the sample. This sample of 4171 observations is called a run. The process is replicated 10,000 times, resulting in a pure random simulation sample of 10,000 runs.

Many studies used a matched sample as the comparison group while conducting event study. Datta et al. (Datta, Iskandar-Datta, & Raman, 2001) select the control firm from pool of firms listed on the same stock exchange if it satisfies the following condition: the sum of the absolute percentage differences between the size, book-to-market ratio, and pre-acquisition price run-up of the sample firm and the matched firm is minimized. This method controls for the specific characteristics of comparable firm, however, it suffers in cross-section effects between the sampled firms. For example, their study results might be contaminated by a rival firm announcement effect (Song & Walkling, 2000a) due to the usage of similar firm characteristics and the exact same time period.

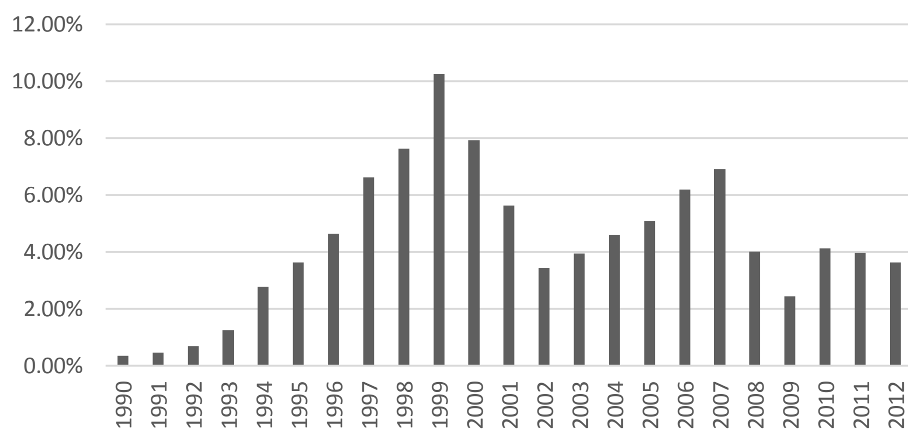
Comparing to a matched sample, a pure random sample (i.e. randomly chosen firms listed on the same stock exchange, randomly chosen pseudo event days from 8041 calendar days) could simulate a more realistic universe which we observe in real life. On another note, oversampling of a certain firm due to replacement should be offset across the 10,000 simulation runs, so the simulation sample will produce a representative sample of actual returns to the firms.

3.2.2. Time Stratified Random Selection Method

As my sample period covers the fifth merger wave from 1994 to 2001, which is driven by market roll-ups, it is inevitable that certain time period is associated with many consolidating deals. Additionally, tech bubble recession taking place around 2000 and subordinate crisis in 2008 are also included in the sample period, leading to strong M&A deal clustering effects. Hence, in order to capture time concentration effect of the takeover deals, a time stratified random selection method is conducted to randomly select combinations from the pool according to the proportions of M&A deals taken place in each year.

Figure 1 shows the weight for each year across the whole sample time period. As we observe, 38% of M&A deals take place during the five-year window of 1997 to 2001, and 17% of M&A deals are clustered in another three-year period from 2006 to 2008. Since major corporate events cluster through time by industry, there is an extensive accounting literature documenting cross-sectional dependence of individual-firm residuals (Mitchell & Stafford, 2000). Although we are taking risks of including potential contaminations in a pure random scenario when adding the time cluster effect into the simulation, two aspects of methodologies mediate the downside: 1) the random selection approach limits industry clustering effect (i.e. each firm-date combination in the same year has equal opportunity to be chosen); 2) relatively short event study window reduces time overlap of individual abnormal returns in the same run. Therefore, the advantage of constructing a time stratified random sample outweighs the risks we take in this study.

Figure 1. Time Concentration for M&A deals from 1990 to 2012[1]



3.3.Event Study Methodology

Standard event study methodology event study methods suggested by MacKinlay (MacKinlay, 1997) has been applied in this study, Cross-Sectional event study for each firm over specified time window is conducted to further examine the magnitude of run-ups and mark-ups. I use Eventus to conduct event studies for both real M&A announcement events and pseudo events in the simulation runs.

Abnormal returns are computed using the following equation:

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt} \qquad (1)$$

Where R_{it} is return for firm i at time t, R_{mt} is the return to the CRSP value-weighted index, $\alpha_i$and β_i are market model parameter estimates from Day 297 through Day 43

[1] The number of M&A deal taking place in each year can be found in Table 13 (See appendix).

prior to the announcement date (or the pseudo announcement date). For each acquiring firm, the cumulative abnormal return is computed as the sum of its abnormal returns during each event window. Following previous studies, event windows for computing pre-bid run-ups and post-bid mark-ups are day [-42, -1] and day [0, +126 or delisting day], respectively.

4. Pre-bid Run-ups Analysis

4.1. How Big is the Run-up

First, standard daily event study has been conducted to investigate the magnitude of pre-bid run-ups in our M&A sample. Since we focus on the pre-bid period, only daily average abnormal returns (AAR) during day [-42,-1] are listed in Table 2. Significance tests are conducted for each daily AAR (PATELL, 1976). First impression from the standard event study shows that, starting on day -40, the targets start to obtain significant abnormal returns. Although significantly different from zero, the observed daily AARs of target stock price remain relatively small in magnitude with a value of 7.68% over day [-42, -1], as comparing to the huge jump of 15.38% on the event day only. Accordingly, mark-up hits a significant cumulative average abnormal return (CAAR) of 21.65%. These findings are in accord with previous researches in the 1980s or earlier. Nevertheless, the magnitude of run-up seems less exciting than that has been recorded by Schwert (1996). For instance, different from his conclusion drawn from an M&A sample covering the time period between 1975 to 1991 (Schwert, 1996) that 50% of control premium is consisted of pre-bid run-ups, here we only observe a run-up accounting for 26% of the total premium.

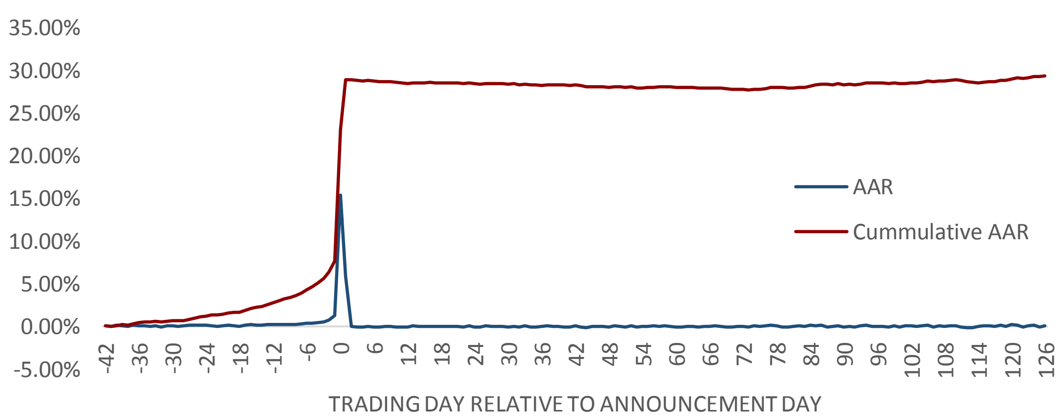
To further investigate pre-bid run-ups of each firm over an event window of day [-42,-1], I also conduct cross-sectional event study to analyze the cumulative abnormal return (CAR) of the targets one by one. Results of the cross-sectional event study for takeover announcement indicate a large cumulative abnormal return with a mean of 7.40% and a median of 5.055% (See Table 3).

Table 2. Abnormal Return for M&A Sample

Day	AAR	Positive : Negative	Patell Z	Cumulative AAR
-42	0.05%	2043:2237	1.316$	0.05%
-41	-0.01%	1987:2293	-0.550	-0.01%
-40	0.12%	2046:2234	2.911**	0.11%
-30	0.05%	2049:2231	0.333	0.68%
-20	0.16%	2067:2213	3.459***	1.58%
-15	0.16%	2094:2186	3.519***	2.24%
-14	0.12%	2056:2224	1.459$	2.36%
-13	0.20%	2131:2148	4.146***	2.56%
-12	0.20%	2092:2188	3.582***	2.76%
-11	0.26%	2106:2174	3.951***	3.02%
-10	0.19%	2108:2172	3.603***	3.21%
-9	0.19%	2080:2200	3.422***	3.40%
-8	0.21%	2113:2167	3.640***	3.61%
-7	0.32%	2138:2142	5.993***	3.93%
-6	0.36%	2155:2125	7.124***	4.29%
-5	0.36%	2195:2085	7.084***	4.65%
-4	0.46%	2226:2054	9.716***	5.11%
-3	0.49%	2204:2076	10.791***	5.60%
-2	0.77%	2270:2010	15.127***	6.37%
-1	1.31%	2427:1850	27.344***	7.68%
0	15.36%	3378:899	359.146***	23.04%
1	5.85%	2592:1685	137.907***	28.89%
126	0.06%	663:720	0.473	29.33%

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> etc. correspond to $,* and show the direction and significance of the generalized sign test.

Figure 2. Target Stock Return around Takeover Announcement

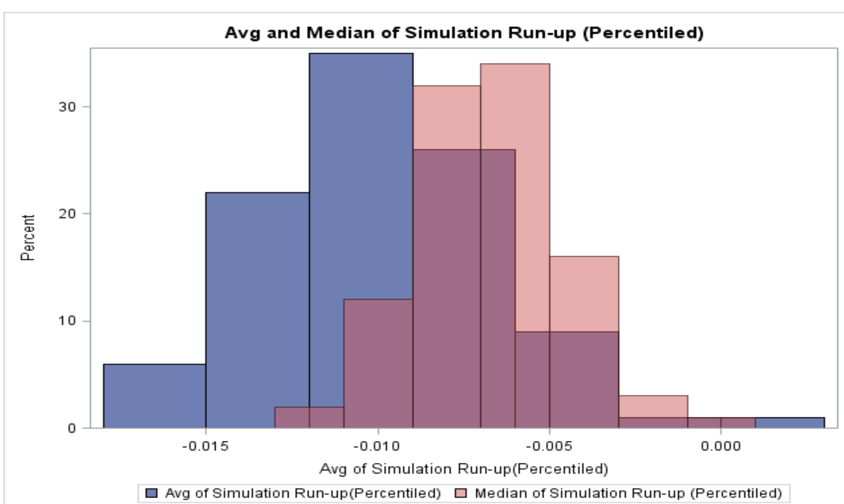


4.2. Mean/Median CARs for Each Simulation Run

As stated above, the mean and the median of CARs for M&A sample (namely 7.4% and 5.1%, see Table 3) are significantly positive, and also very close to its 7.68% cumulative average abnormal return under standard event study method (see Section 4.1). It consists with findings in Franks and Harris (1989) that there is 8.4% CAR over the 4 months before M&A announcement. However, an average cumulative run-up of 13.3% has been recorded in the research of Schwert (1996), while Betton, Eckbo and Thorburn (2008) found an average target run-up of 8.3% over day [-42, -1] during 1980 – 2002 using a sample similar to the that used in this study. These evidences have manifested the dispersions on the magnitude of pre-bid run-up over time.

Instead of a zero average mean (median) as we expect, in Figure 3 and Table 3 we could observe a negative average value of -0.0102 for means of CARs crossing 10,000 simulation runs derived from pure random simulation sample (-0.0098 for time stratified simulation sample). This finding seems to suggest that investors, on average, are losing money over the 23-year horizon.

Figure 3. Frequency of Means (and Medians) of Each Simulation Run[2]



[2] To make the figure easier to observe, the 10,000 means (medians) of simulation runs have been ordered into percentiles first, then plot the probability distribution for the distribution.

Table 3. Descriptive Statistics of Average of Mean CARs for Simulation Run

	N	Pure Random Simulation	Obs at 95th Percentile	Std. Deviation	Time Stratified Random Simulation	Std. Deviation	Obs at 95th Percentile
Avg. of Mean CARs from Each Run	10000	-0.0102	-0.0047	0.0033	-0.0098	0.0035	-0.0041
		(-3.0944**)			(-2.7980**)		
Avg. of Median CARs from Each Run	10000	-0.0068	-0.0035	0.0021	-0.0068	0.0021	-0.0033
		(-3.2902**)			(-3.1830**)		
Mean CAR for M&A	4171	0.0740		0.2422			
		(19.7218***)					
Median CAR for M&A	4171	0.0505		0.2422			
		(<.0001***)					

Test for Null Hypothesis: Mu0=0 using population std. deviation, to calculate t-stat using sample std. deviation, simply times t-stat in parenthesis by $\sqrt{N}$=100;
Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1];
Student's t Test for Mean (T-Stat), Signed Rank Test for Median (P-Value);
The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively; using a two-tail test.

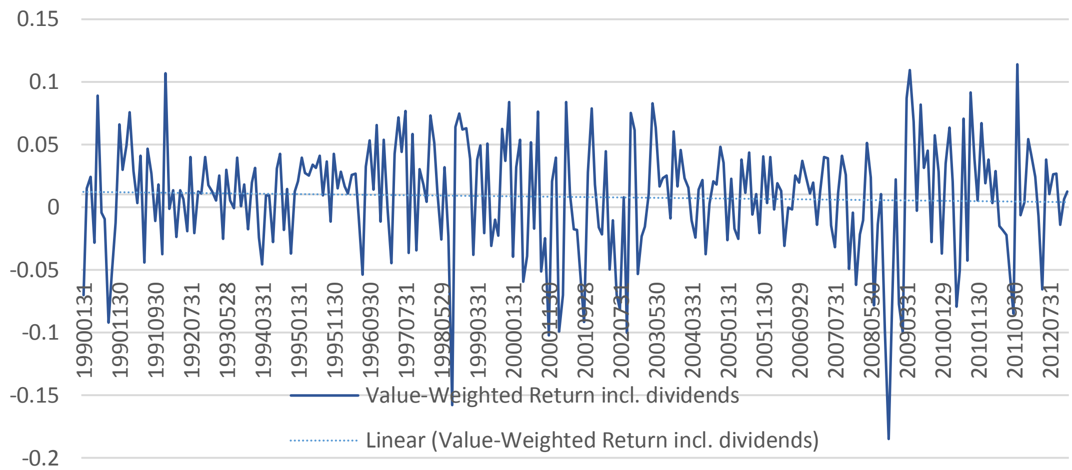
It is necessary to point out that, for the average of 10,000 mean (median) CARs, t-statistic calculated using sample standard deviation is unusually big due to its large sample size (Table 3). It has been noticed that, p-values go quickly to zero in very large samples, and could even make minuscule effects become statistically significant (Lin, Lucas Jr., & Shmueli, 2013; Schervish, 1990). Here I use the population standard deviation to recalculate the t-statistic for simulation samples. Adjusted t-statistics (in parenthesis) are still significant at 5% level, suggesting no strong evidence for bias in the results. To get unadjusted t-statistic, simply times them by $\sqrt{N}$ (here $N = 10{,}000$).

In order to find possible explanations for the negative average means (medians) of the simulation CARs, a good understanding of the market is indispensable. Since the Value-Weighted CRSP Market Index (combined NYSE, AMEXT, NASDAQ, and ARCA exchanges) is used in the cross-sectional event study, we expect to have a big picture of the market trend in this period by analyzing market index returns. Therefore, I checked the CRSP value-weighted (include dividends) monthly market returns from Jan 1990 to Dec 2012. As shown in Table 5, although 37.68% of the months have negative returns, the average market return crossing 23 years hits a positive 0.008 which is small in magnitude but significantly different from zero.

Table 4. CRSP Value-Weighted Market Returns during 1990-2012

Date of Observation	Value-Weighted Annual Average Return
1990	-0.0039
1991	0.0253
1992	0.0075
198	0.0093
1994	-0.0002
1995	0.0259
1996	0.0166
1997	0.0232
1998	0.0190
1999	0.0197
2000	-0.0083
2001	-0.0081
2002	-0.0178
2003	0.0246
2004	0.0105
2005	0.0062
2006	0.0128
2007	0.0063
2008	-0.0371
2009	0.0249
2010	0.0151
2011	0.0002
2012	0.0127
No. of Months	276
Avg. Market Return	0.0080
Median Market Return	0.0134
% Negative	0.3768
Std. Deviation	0.0449
T Stat (Mu=0)	2.9658

Figure 4. Value-Weighted Return including dividends



Major stock price movements caused by the dot.com bubble crashing around 2000 and the subordinate crisis in 2008 are clearly displayed in Figure 4. Each of the two crises alone has brought huge negative impact to the market (-0.0343 and -0.371, respectively).

There are three possible explanations for the negative CAR means (medians), on average, across 10,000 simulation runs. First of all, we need to understand that the random selection method includes all the 276 months, thus it loses any effects of variation through time despite due to the large sample size it has. It is not unexpected that event study for exchange-listed firms scattered all over in different time periods (with replacement) results in an average CAR mean (median) that is slightly different from the market trend. A good example can be found is that, after considering time concentration effect of M&A deals (i.e. their influence on the market return), time stratified sample outputs a less negative average CAR mean (median), which is more close to zero.

Secondly, the sample used in this paper does not include firms trading on Arca Stock Market (SM), which may cause slight dispersions as well.

Finally, we have to take firm size into account. Since our sample excludes all the companies with a market cap smaller than 10 million dollars on the day of -42, and that smaller firms have higher risk adjusted returns, on average, than larger firms (Banz, 1981), it is possible that the market outperforms the simulation sample for about 1%.

4.3. Examination of Pre-bid Run-up at Selected Percentiles

Comparison between the cross-sectional cumulative abnormal return of the M&A sample and the simulation sample will cast lights on how big the problem is for real pre-bid run-ups.

To be more specific, the purpose of my comparison study is to find direct evidence of the true target pre-bid run-ups, especially after considering the magnitude of pseudo run-ups, or "normal" stock price volatility level generated from a pure random simulation.

While conducting the cross-sectional event study for each takeover target over the period of day [-42,-1], I captured pre-bid target price increases which have been documented in many researches. Following the method used by Fama & French (2010), with a few modifications, I divided this cross-section cumulative abnormal return into percentiles and ordered it into a probability distribution function (PDF) according to the frequency and the magnitude of the run-up CARs.

Approach applied to divide the percentiles is described below (Definition 3 in SAS system[3]):

Let n equals the number of nonmissing values for a variable, and let $x_1, x_2 \ldots x_n$ represent the ordered values of the process variable. For the t^{th} percentile, set $\mathrm{p} = \mathrm{t}/100$, and express $n\mathrm{p}$ as

$$n\mathrm{p} = \mathrm{j} + \mathrm{g}$$

[3] This definition can be found in SAS Online Doc 9.1.3 http://support.sas.com/onlinedoc/913/docMainpage.jsp

Where j is the integer part of np, and g is the fractional part of np.

The t^th^ percentile (call it y), using the empirical distribution function, is defined in the following way.

$$\begin{cases} y = X_j, & if\ g = 0 \\ y = X_j + 1, & if\ g > 0 \end{cases}$$

Following this method, similar PDFs can be generated for the pseudo CARs of each simulation run at selected percentiles. Thus, a distribution of the averages at selected percentiles across 10,000 simulation runs could be obtained by us for comparison study.

In my initial investigation, I compare the values of CAR [-42,-1] at selected percentiles of the PDF from real takeover sample and the averages across 10,000 simulation runs at the same percentiles.

Furthermore, I constructed the standardized CAR for both M&A sample and the two simulation samples. The comparison using standardized CAR between the three samples will reflect more information having variance under control.

The cumulative abnormal return (CAR) to firm j over event period t is $CAR_{jt} = \sum_{t=T1}^{T2} AR_{jt}$, where T_1 (T_2) denotes the beginning (ending) day of the event window. The Standardized CAR is defined as:

$$SCAR_{jt} = CAR_{jt}/S_{CAR_{jt}}$$

Where $S_{CAR_{jt}}$ is the standard deviation of CAR_{jt} , and each $SCAR_{jt}$ follows a student's t distribution under the null hypothesis that each CAR_{jt} has a mean of zero and variance of $S^2{}_{CAR_{jt}}$.

The initial examination for the probability distributions of CAR derived from different samples seems very interesting (see Table 5). An average simulation 95th percentile CAR of 0.3172 is, in fact, larger than 90% of CARs in real M&A case; on the other hand, less than 3% of real M&A CARs are smaller than the first 5% of the average simulation CARs. All these empirical findings cast doubts on the significance of real M&A CARs when they are compared with simulation ones.

If we imagine the empirical distribution of random simulation CARs as the population distribution, or a huge "background" where we mix both noises (abnormal returns involved with private information) and market portfolio movements (i.e. macro-economic movements), it is not farfetched to reason that, as comparing to a simple benchmark of zero, this empirical distribution is much closer to our real-life scenario. Moreover, it could help us to draw valuable inferences for the discussion on the magnitude of pre-bid run-ups.

That being said, instead of only testing null hypothesis $H_0: CAR = 0$, I also conduct a two-sided test using empirically derived critical values for the real M&A CARs (use average simulation 5^{th} CAR of -0.3463 as critical value for the M&A CARs with negative signs, whereas average simulation 95^{th} CAR of 0.3172 is used for the M&A CARs with positive signs). Table 5 displays critical percentiles of CARs for the three samples, results from traditional t-test for M&A CAR at each percentile, and the t-statistics for comparison between empirically derived critical values and M&A CARs. Also, I report the proportion of 10,000 simulation CARs at 5^{th} (95^{th}) percentile that are larger (smaller) than M&A CAR at selected percentiles. Note that only when the t-statistics derived from t-tests with null hypothesis $H_0: average\ 5^{th}(95^{th})CAR_{simu} > CAR_{M\&A}$, where $CAR_{M\&A} < 0$ ($CAR_{M\&A} > 0$) are significant with corresponding signs could we consider M&A CAR at selected percentile is smaller (larger) than the average simulation 5^{th} (95^{th}) percentile. For example, for the M&A CAR at 1^{st} percentile with a negative sign, t-statistic denoted by $t = \frac{(average\ 5^{th}\ CAR_{simu} - 1^{st} CAR_{M\&A})}{\sigma_{5^{th} CAR_{simu}}}$ should be positively significant if null hypothesis is accepted; on the contrary, for the M&A CAR at 90^{th} percentile with a positive sign, t-statistic should be negatively significant when we reject the null hypothesis that average 95^{th} simulation CAR is larger than the selected M&A CAR, and accept the alternative hypothesis that selected M&A CAR is larger than the average 95^{th} simulation CAR.

Table 5. Pseudo vs. Real Target Pre-bid Run-ups at Selected Percentiles (across 10, 000 Runs)

M&A*, *Pure Random, and ***Time Stratified Random*** list the CARs from each sample at 100 percentiles. ***T-stat (H_0: M&A CAR=0)*** displays the t-statistics for t-test with null hypothesis of $H_0: CAR_{M\&A} = 0$ for the M&A CAR at each percentile. ***vs 5th (95th) Percentile of Simulation*** compares M&A CAR at selected percentile with average simulation CAR at 5th (95th) percentile if M&A CAR has a negative sign (positive sign). ***<% 5th or > % 95th Pure Random*** denotes the proportion of 10,000 simulation CARs at 5th percentile that are larger than M&A CAR at selected percentile, or proportion of 10,000 simulation CARs at 95th percentile that are smaller than M&A CAR at selected percentile. ***T-stat (H0: Simu 5th (95th) >M&A)*** denotes the t-statistics from t-tests with null hypothesis of $H_0: average\ 5^{th}(95^{th})CAR_{simu} > CAR_{M\&A}$, where $CAR_{M\&A} < 0$ ($CAR_{M\&A} > 0$), standard deviation used for tests involving with average simulation 5th CAR is $\sigma = \sqrt{\frac{1}{10,000}\sum_{i=1}^{10,000}(Simu\ Pct5_i - \mu)^2}$, where $\mu = \frac{1}{10,000}\sum_{i=1}^{10,000} Simu\ Pctl5_i$. Same formula applies when calculating standard deviation used for tests with average simulation 95th CAR. Note that population std. deviation is used while calculating ***T-stat (H0: Simu 5th (95th) >M&A***, simply times them by $\sqrt{N}$=100 to get t-stats using sample std. deviation

Percentile	M&A	T-stat (H0: M&A CAR=0)	Pure Random	vs 5th (95th) Percentile Pure Random	<% 5th or > % 95th Pure Random	T-stat (H0: Simu 5th (95th) >M&A)	Time Stratified Random	vs 5th (95th) Percentile Time Stratified Random	<% 5th or > % 95th Time Stratified Random	T-stat (H0: Simu 5th (95th) >M&A)
pct1	-0.5360	-142.9631***	-0.6436	<	100.00	***6.4036****	-0.6661	<	100.00	***5.6624****
pct2	-0.4315	-115.0809***	-0.5098	<	100.00	***4.2944****	-0.5260	<	100.00	***3.6386****
pct3	-0.3499	-93.3298***	-0.4366	<	63.06	0.2324	-0.4485	>	32.20	-0.3371
pct4	-0.2983	-79.5741***	-0.3851	>	0.00	-3.7138	-0.3960	>	0.00	-4.0886
pct5	-0.2633	-70.2375***	***-0.3463***	>	0.00	-7.4409	***-0.3555***	>	0.00	-7.7163
pct10	-0.1710	-45.5977***	-0.2338	>	0.00	-25.0097	-0.2384	>	0.00	-24.8557
pct20	-0.0804	-21.4410***	-0.1309	>	0.00	-62.4764	-0.1325	>	0.00	-62.0427
pct30	-0.0293	-7.8134***	-0.0754	>	0.00	-102.8317	-0.0759	>	0.00	-102.2696
pct40	0.0088	2.3406**	-0.0371	<	0.00	125.3989	-0.0372	<	0.00	124.3009
pct50	0.0505	13.4822***	-0.0069	<	0.00	128.6262	-0.0068	<	0.00	129.4243
pct60	0.0951	25.3531***	0.0211	<	0.00	100.3534	0.0213	<	0.00	101.2549
pct70	0.1492	39.8090***	0.0558	<	0.00	59.5741	0.0566	<	0.00	60.2363
pct80	0.2302	61.4051***	0.1076	<	0.00	21.9150	0.1096	<	0.00	23.0128
pct90	0.3525	94.0096***	0.2062	>	99.87	***-5.1668****	0.2111	>	98.56	***-3.5608****
pct95	0.4837	129.0084***	***0.3172***	>	100.00	***-14.8066****	***0.3266***	>	100.00	***-13.3167****
pct96	0.5302	141.4281***	0.3559	>	100.00	***-16.2447****	0.3669	>	100.00	***-14.7649****
pct97	0.5753	153.4597***	0.4079	>	100.00	***-16.1813****	0.4197	>	100.00	***-14.7606****
pct98	0.6549	174.6775***	0.4833	>	100.00	***-16.1437****	0.5007	>	100.00	***-14.6107****
pct99	0.7796	207.9424***	0.6265	>	100.00	***-14.2537****	0.6523	>	100.00	***-12.9278****
pct100	2.2632	603.6716***	2.2418	>	100.00	***-1.8344$***	2.4232	>	100.00	***-1.6027***

Table 5 Continued. Standard Pseudo Target Pre-bid Run-ups at Selected Percentiles (across 10, 000 Runs)

PCTL	Std. M&A	Std. Pure Random	Difference[4]	M&A vs 5th (95th) Percentile of Simulation 1	Std. Time Stratified Random	M&A vs 5th (95th) Percentile of Simulation 2
pct1	-1.7412	-2.1881	0.4469	<	-2.1378	<
pct2	-1.4016	-1.7330	0.3314	<	-1.6883	<
pct3	-1.1367	-1.4844	0.3477	>	-1.4395	>
pct4	-0.9692	-1.3090	0.3398	>	-1.2712	>
pct5	-0.8554	***-1.1773***	0.3219	>	***-1.1410***	>
pct10	-0.5554	-0.7949	0.2396	>	-0.7652	>
pct20	-0.2611	-0.4451	0.1839	>	-0.4254	>
pct30	-0.0952	-0.2564	0.1612	>	-0.2436	>
pct40	0.0285	-0.1260	0.1545	<	-0.1194	<
pct50	0.1642	-0.0233	0.1875	<	-0.0218	<
pct60	0.3088	0.0717	0.2371	<	0.0684	<
pct70	0.4848	0.1898	0.2951	<	0.1817	<
pct80	0.7479	0.3659	0.3820	<	0.3519	<
pct90	1.1450	0.7010	0.4439	>	0.6774	>
pct95	1.5712	***1.0784***	0.4929	>	***1.0484***	>
pct96	1.7225	1.2101	0.5124	>	1.1776	>
pct97	1.8690	1.3867	0.4823	>	1.3470	>
pct98	2.1275	1.6431	0.4843	>	1.6071	>
pct99	2.5326	2.1299	0.4027	>	2.0937	>
pct100	7.3523	7.6212	-0.2689	>	7.7777	>

Standard CAR is defined as $SCAR_{jt} = CAR_{jt}/S_{CAR_{jt}}$;

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1];

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

Find CARs and tests for all percentiles in Table 16, 17 (See Appendix)

[4] Denotes the difference between Std. M&A and Std. Pure Random.

Also note that I use population standard deviation to calculate t-statistics to mediate the effect of large sample size which has been discussed in the previous section; to get unadjusted t-statistic, simply times them by $\sqrt{N}$ (here $N = 10{,}000$). Back to the discussion about the magnitude of M&A run-ups, inferences drawn from the empirically derived critical values suggest that only M&A CARs that are smaller than average 5th CAR_{simu} (or larger than average 95th CAR_{simu}) should be recognized as abnormal. More detailed results of comparison for CARs at all the 100 percentiles can be found in Table 16 in the Appendix.

According to the empirically derived benchmark, only 13% of CARs in M&A run-up distribution (this fraction equals 13% when comparing to Pure Random Simulation, and equals 12% when comparing to Time Stratified Random Simulation) fall into the extreme areas of the empirical distribution (the upper and the lower 5%). That is to say, using the empirical distribution of pure random simulation CARs as the benchmark, we can conclude with 90% confidence that around 13% of real M&A CARs are significantly different from the average CAR under the normal scenario, whereas tests for $H_0: CAR = 0$ all conclude in rejection of the null hypothesis. This finding brings up a warning signal that traditional t-test with benchmark of zero might reject the null hypothesis too often (type I error).

Provided the discussion above, it is necessary for us to reconsider how big the run-up should be before we could say they are "abnormal". If we use empirical simulation distribution as the benchmark, we should have CAR at 5th percentile and that at 95th percentile as the two critical values. In this case, all the run-ups that are smaller than -0.03463 or larger than 0.3172 will be safely considered to be abnormal.

Further examination for standard CARs at selected percentiles of all the three samples agrees with the previous conclusion I draw. As demonstrated in Table 5, after controlling the variance of each sample, 14% of M&A CARs could be considered to be abnormal using the standard simulation CAR (pure random sample) distribution as the benchmark. This similar result has reinforced the discussion above.

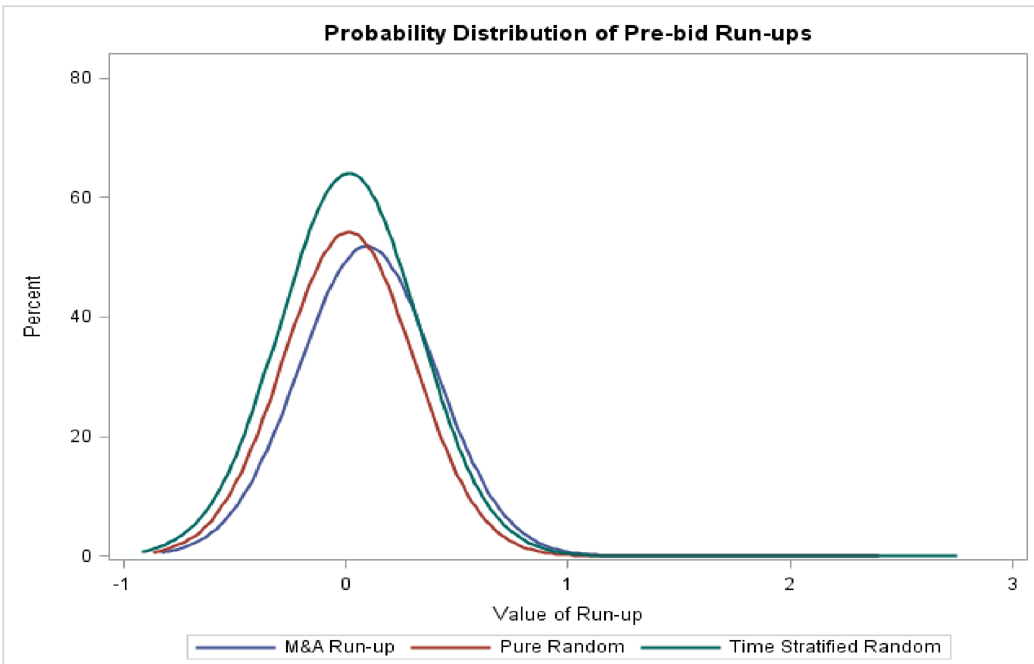
Figure 5 implies that distribution of M&A run-ups has horizontally translated towards the right, to an extent, indicating there are more above-zero CARs in general, in other words, there are more extreme values fall into the right tail. Discussion about the average of CAR means in Section 4.2 consists with this deduction as we observe a slight below-zero average of CAR means across 10,000 simulation runs whereas a positive average of M&A CARs. However, as we could observe from Figure 5, there is an overlap between the majority of M&A run-up distribution and random simulation run-up distributions, suggesting large proportion of M&A run-ups do not fall beyond the empirically derived critical values.

Concerns about using the empirical distribution of simulated run-ups as testing benchmark include 1) random selection approach used in the simulation sample and 2) influence of firm specific characteristics.

First, potential concern about simple random selection method described in Section 3.2.1 reasons that this method mixes all the firm-date combinations with replacement across time, thus it cannot reflect the time concentration effect of M&A deals. This concern has been resolved by the time stratified random selection approach. Results of distribution generated by time stratified simulation sample in Table 16 and Figure 5 all offer support to the conclusion brought by the study using pure random sample. To be more specific, only 2% of M&A run-ups are smaller than average 5^{th} CARs of time stratified random simulation, and 10% of M&A run-ups are larger than the critical value of average 95^{th} CAR, demonstrating an even smaller proportion of M&A run-ups that could be recognized as abnormal. This evidence is in accord with my anticipation as the time stratified random simulation includes time concentration effect of M&A deals, which is reflected in positive stock price movements, making the compared M&A CARs even less outstanding.

Another concern is that firm specific characteristics might have strong influence, thus it might not be proper to use simulation samples as a comparison group. To understand the reasons for selecting random firm with limited constrains shown in Table 1 (see Section 3.1), we should first keep in mind that the purpose of constructing the random simulation is to mimic an unconditional scenario where mixing all the noises, and this purpose has been achieved by the approach applied in this paper. On the contrary, another traditional method that uses target comparison group suffers from potential contamination caused by M&A announcement effect in the same industry. Song & Walkling (2000) found that both rival firms and portfolios of rival firms earn significantly positive abnormal returns for an initial industry acquisition.

Figure 5. Probability Distribution of Run-ups at Selected Percentiles (across 10,000 Runs)



In conclusion, it is suggested by the findings that there is certain advantage for us to revise traditional study approach and consider distribution of random simulation run-ups as a potential benchmark while studying pre-bid run-ups.

5. Relations between Pre-bid Run-ups and Post-bid Mark-ups

To answer the question that how pre-bid run-ups affect total control premium, I follow Schwert (1996) and Betton, Eckbo and Thorburn (2008) to examine relation between run-ups and mark-ups using OLS regression model. Additionally, in this section my study moves forward to the empirical b estimates distribution analysis, and the results provide new evidence for the relation between run-ups and mark-ups in a random situation (i.e. no predictable M&A announcement is coming on the way).

While testing the substitution hypothesis and mark-up pricing hypothesis mentioned in Section 2, simple linear regression model could be established as:

$$\mathrm{Premium}_i = \mathrm{a} + \mathrm{b}\ \mathrm{Runup}_i + u_i \qquad (2)$$

Under Substitution Hypothesis, estimate of b equals to zero since pre-bid run-ups have no effect on total premium; on the contrary, estimate of b should rounds up to one if Mark-up Pricing Hypothesis applies because each dollar in the run-ups will add up into the final control premium.

From Schwert's (Schwert, 1996) formula we could know that $Premium = Runup + Markup$. Equation (1) could therefore be transferred into the following format:

$$\mathrm{Markup}_i = \mathrm{a} + (\mathrm{b} - 1)\ \mathrm{Runup}_i + u_i \qquad (3)$$

Derived from equation (3), equation (4) is simpler and could be used directly for testing the two competing hypotheses.

$$\mathrm{Markup}_i = \mathrm{a} + \mathrm{b}\ \mathrm{Runup}_i + u_i \qquad (4)$$

Testing hypotheses can be described accordingly using equation (4):

Substitution Hypothesis: Pre-bid run-ups offset post-bid mark-ups one for one (the mark-up is lower by the run-up by the same amount), the coefficient b in regression (4) equals -1.

Mark-up Pricing Hypothesis: Pre-bid run-ups increase the final control premium one for one, and coefficient b in regression (4) equals 0.

In addition, if coefficient b ranges between -1 and 0, then it is considered to be a partial substitution where part of the pre-bid run-ups transfer into the final premium.

As discussed in Section 2, although Schwert (1996) provided support for the mark-up pricing hypothesis with a coefficient of 0.1300 (adjusted to Equation (4) in this paper), Betton, Eckbo & Thorburn (2008) observed a different coefficient of 0.5950, which implied a strong relation between run-ups and mark-ups. To further study this puzzle, this paper replicates regression analysis conducted by the two articles mentioned above, but looking through a different perspective – what is the "normal" relation between hypothetic run-ups and mark-ups if no predictable event taking place. That is to say, whether the relation between run-ups and mark-ups under an M&A scenario is stronger than that under the normal scenario. The establishment of empirical benchmark representing normal scenario has, in my opinion, major contribution to the debate upon substitution hypothesis and mark-up pricing hypothesis.

5.1.Single Factor Regression

Two random simulation samples (see Section 3.2) and the M&A sample are examined using single-factor OLS model denoted by equation (4).

I report the average intercept estimates as well as b estimates using data from the 10,000 simulation runs, and list the average t-statistic in parenthesis. T-test has been conducted to testify whether the average coefficient is significantly different from zero. Note that I also use population standard deviation to calculate t-statistics here, and unadjusted t-statistic can be get by simply times them by $\sqrt{N}$ (here $N = 10{,}000$). The percentage of t-statistics that are significant at 5% level is also reported in the following table (Table 6). It is more reliable to consider both inferences in order to have a better judgement of the significance and explaining power of the coefficient. For example, if more than 95% of regression t-statistics for the b coefficient are significantly different from zero, it is safer for us to conclude that the run-up is of significant influence on the mark-up. Last but not least, a two-sample t-test has been conducted for b coefficients, which is of great importance while comparing results between two samples.

Firstly, I compare the b coefficient from regression using M&A sample with findings in previous studies. Similar with the 0.13 (has been adjusted by Equation (4)) in Schwert (1996), single factor regression model outputs an estimate of 0.1753, significant at 1% level. Only judging from this b coefficient, we will logically accept the mark-up pricing hypothesis, just as Schwert (1996) did, as the b coefficient is more close to zero comparing to minus one. Under this hypothesis, mark-ups are barely affected by the run-ups, and the total control premium (denoted as $Premium = Runup + Markup$) will therefore increase as pre-bid run-ups occur.

Nevertheless, doubts still exist for this argument: 1) the coefficient is significantly larger than zero, which does not apply for the [-1, 0] range suggested by the two competing hypotheses; 2) similar study conducted by Betton, Eckbo & Thorburn (2008) has found a coefficient of 0.5950, which also mediates the robustness of the conclusion made by Schwert (1996).

As to the b coefficient outputted by regression using random simulation samples, it is obvious that average b estimates across 10,000 simulation runs, rounding to 0.4674, is significantly larger than the 0.1753 we get from M&A sample. Two-sample t-test with null hypothesis that there is no significant difference between the mean of b coefficient in simulation sample and the b coefficient in M&A sample reports a significant t-statistic in Table 6. This makes our discussion quite interesting as 0.4674 represents the “norm” and should be used as the baseline in a coordinate system if we intend to test the two competing hypotheses (see Figure 6).

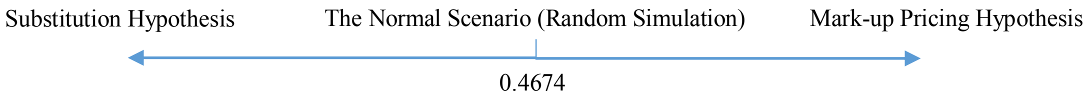
Table 6. Single Factor Regression Results

Pure Random and ***Time Stratified Random*** represent the regression coefficient from the two simulation samples, which is the average of coefficients across 10,000 runs. ***% T Sig.*** shows percentage of t-statistics derived from regression in each run that are significant at 5% level using a two-tail test. ***T-stat (H_0: Mu=0)*** displays results of t-test examining whether the corresponding coefficient is significantly different from zero. Note that population std. deviation is used while calculating ***T-stat (H_0: Mu=0)***, simply times them by $\sqrt{N}$=100 to get t-stats using sample std. deviation. ***T-stat (H_0: Mu_{Simu}=$Mu_{M\&A}$)*** presents results from two-sample t-test with a null hypothesis that there is no significant difference between the mean of b coefficient in simulation sample and the b coefficient in M&A sample.

	N	Pure Random	% T Sig.	T-stat (H_0: Mu=0)	T-stat (H_0: Mu_{Simu}=$Mu_{M\&A}$)	Time Stratified Random	% T Sig.	T-stat (H0: Mu=0)	T-stat (H_0: Mu_{Simu}=$Mu_{M\&A}$)
					Simulation Runs				
Intercept	10000	-0.0207				-0.019			
		(-2.6985)	87.3	(-3.12**)		(-3.1149)	77.96	(-2.77**)	
CAR [-42,-1]	10000	0.4674				0.4621			
		(14.8176)	100	(6.87***)	(429.37***)	(15.3901)	100	(6.78***)	(421.57***)
					M&A Sample				
Intercept	4171	0.1913	n/a			n/a			
		(29.4757***)							
CAR [-42,-1]	4171	0.1753	n/a			n/a			
		(6.8376***)							

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]; Mark-ups are estimated over day [0, +126 or delisting day];
T-stats are in parentheses, the symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

Figure 6. Suggested Relationship between Run-ups and Mark-ups



As presented by Figure 6, I expect a value of b coefficient larger than the baseline in order to offer support for mark-up pricing hypothesis and vice versa. The establishment of this coordinate system with new baseline suggest that more discussions should be made before we could come to a safe conclusion about the two competing hypotheses.

5.2. Multiple Regression

To further examine other potential explanatory factors that might have influence on the regression model, a multiple OLS regression has been conducted following Equation 5.

$$\mathrm{Markup}_i = \mathrm{a} + \mathrm{b}\ \mathrm{Runup}_i + \mathrm{c}\ Size_i + d\ Exchange_i + eSIC_i + u_i \qquad (5)$$

Where $Size_i$ is the size of the firm, denoted as the logarithm of market capitalization on day -42.

$Exchange_i$ is a dummy variable representing the stock exchange where the firm lists on: it equals 1 when the firm lists on NYSE and AMEX, and equals 0 when the firm lists on NASDAQ.

SIC_i denotes industry characteristics using the first two digits of the four-digit Standard Industrial Classification code.

Previous studies have noticed that smaller firms are more likely to become targets (Mikkelson & Partch, 1989), and they enjoy higher risk adjusted returns (Banz, 1981). From an opposite perspective, it is likely that larger targets have less information asymmetry, and it may be more difficult to detect any insider information about larger targets (Brigida & Madura, 2012; Meulbroek, 1992). Therefore, it is expected that variable of $Size_i$ will have a negative sign for its coefficient. Since this study use a firm sample that is mixed across different stock exchanges and industries, I examine the potential effect brought by these two factors in order to get a more robust result for relation between run-ups and mark-ups.

From results presented in Table 7 we could safely conclude that, other than the positively significant run-ups, only firm size has shown a significantly negative relation with mark-ups, which consists with the previous expectations that larger firms tend to have lower probability of becoming target, less information asymmetry, and they enjoy less positive abnormal returns. Additionally, 79% of t-statistics for stock exchange coefficient are significant, indicating a weak influence caused by the different characteristics of stock exchange.

More importantly, results exhibit that the two run-up coefficients for pure random sample and time stratified random sample are 0.46 and 0.45, respectively. Both b coefficients are significant at 1% level. On another note, the b coefficient of 0.1507 for the M&A sample is also very close to what we get from single factor regression model. These findings indicate that single factor model is of good explanatory power, and using multi-factor model does not cause any substantial change for the previous results.

In order to better understand b estimates for the 10,000 simulation runs, it is necessary to investigate empirical b estimate distribution derived from simulation samples. Table 8 summaries simulation b estimates from both single-factor and multiple regression models. Provide that all the simulation b estimates (even b estimate at the 1st percentile) are larger than the 0.1753 from M&A single-factor regression in this paper and also the 0.13 in the study of Schwert (1996), we could therefore agree with the discussion in Section 5.1. Moreover, two-sample t-test for the difference of mean between b estimates from M&A sample and the two simulation samples all conclude that the relation between run-ups and mark-ups under the normal scenario is significantly stronger than that under the M&A scenario.

Table 7. Multiple Regression Results

Pure Random and ***Time Stratified Random*** represent regression coefficients from two simulation samples, which average coefficients across 10,000 runs. ***% T Sig.*** shows percentage of t-statistics derived from regression in each run that are significant at 5% level. ***T-stat (H_0: Mu=0)*** displays results of t-test examining with null hypothesis *H_0: Mu=0*. Note that population std. deviation is used while calculating ***T-stat (H_0: Mu=0)***, simply times them by $\sqrt{N}$=100 to get t-stats using sample std. deviation. ***T-stat (H_0: Mu_{Simu}=$Mu_{M\&A}$)*** presents results from two-sample t-test with a null hypothesis that there is no significant difference between mean of b coefficient in simulation sample and b coefficient in M&A sample.

	N	Pure Random	% T Sig.	T-stat (H0: Mu=0)	T-stat (H_0: Mu_{Simu}=$Mu_{M\&A}$)	Time Stratified Random	% T Sig.	T-stat (H0: Mu=0)	T-stat (H_0: Mu_{Simu}=$Mu_{M\&A}$)
				Simulation Runs					
Intercept	10000	0.1853				0.2155			
		(3.6292)	94.17	(3.37***)		(3.9500)	96.97	(3.70 ***)	
CAR [-42,-1]	10000	0.4600				0.4542			
		(15.1658)	100	(6.75***)	(453.56***)	(14.5837)	100	(6.65***)	(444.28***)
Size	10000	-0.0188				-0.0203			
		(-4.8361)	99.87	(-4.96***)		(-4.9310)	99.89	(-5.08***)	
Stock Exchange	10000	0.0388				0.0388			
		(2.7527)	78.95	(2.81**)		(-2.5991)	74.31	(2.67**)	
Industry	10000	0.0001				-0.0000			
		(0.3832)	8.30	(0.36)		(-0.0603)	6.97	(-0.06)	
				M&A Sample					
Intercept	4171	0.6104				n/a			
		(11.03***)							
CAR [-42,-1]	4171	0.1503				n/a			
		(5.86***)							
Size	4171	-0.0298				n/a			
		(-6.91***)							
Stock Exchange	4171	0.0117				n/a			
		(0.76)							
Industry	4171	-0.0010				n/a			
		(-3.09**)							

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]; Mark-ups are estimated over day [0, +126 or delisting day];
The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

Table 8. b Estimates Distribution at Different Percentiles

Percentile	Single Factor Regression: Pure Random	Single Factor Regression: Time Stratified	Multiple Regression: Pure Random	Multiple Regression: Time Stratified
1	0.3190	0.2960	0.3114	0.2887
5	0.3638	0.3557	0.3555	0.3477
10	0.3856	0.3797	0.3783	0.3712
25	0.4220	0.4170	0.4149	0.4092
50	0.4636	0.4609	0.4561	0.4530
75	0.5083	0.5041	0.5012	0.4960
90	0.5528	0.5473	0.5460	0.5402
95	0.5858	0.5762	0.5786	0.5688
99	0.6482	0.6340	0.6413	0.6273
100	0.8361	0.7498	0.8304	0.7419

Another important finding is that simulation b estimate at 95th percentile is very close to the 0.5950 cited in the research of Betton, Eckbo & Thorburn (2008). If we use the coordinate system suggested in Figure 5 (Section 5.1), findings in Betton, Eckbo & Thorburn (2008) implies that mark-up pricing hypothesis outweighs substitution hypothesis, whereas results in this paper and in Schwert (1996) suggest an opposite case. To sum up, this dispersion may be caused by samples that across different time periods and stock exchanges, which will be further discussed in the following section.

5.3. Stock Exchange Specific Effect

As I mentioned in the previous sections, the sample selection approach in this paper follows the majority of criteria used in Schwert (1996) and Betton, Eckbo & Thorburn (2008). However, due to the difference in sample time period and/or the stock exchange where the firm lists on, we could observe differences in sample size and research results in Table 9.

It seems that b estimate we observe in M&A sample tells us a similar story as Schwert (1996) did, whereas findings from Betton, Eckbo & Thorburn (2008) suggest a much stronger relation, which might be caused by the time period (1980 – 2002) used in their research covering the 4^{th} and 5^{th} merger waves and two recessions[5]. These abnormal market movements may cause strong autocorrelation over certain time periods.

Among all the differences in the sample selection criteria, stock exchange may has relatively strong influence on sample construction, and it will finally affect the results. Therefore, the original simulation pool is divided into two groups – the NYSE & AMEX group containing all the firms listing on these two stock exchanges and the NASDAQ group accordingly. For each group, I construct Pure Random simulation with 10,000 runs follow the approach discussed in Section 3.2. Multiple regression is replicated for simulation runs in each group (see Table 10).

As NASDAQ and NYSE are different in market structure, I expect there is difference between b coefficients using the two different groups. Not surprisingly, the results show that 1) estimation using both samples get b coefficient over 0.4, and 2) b estimate in NASDAQ group shows a larger value of 0.47 and that in NYSE & AMEX group is close to 0.42. Possible explanation could be that NASDAQ stocks are traded by a large number of market venues and have a higher degree of order flow fragmentation than NYSE, which reduce the market quality and price efficiency (Bennett & Wei, 2006).

Nevertheless, with the slight difference involved in the regression result from two groups divided by stock exchange, previous conclusion will not be changed.

5.4. Substitution Effect

As we know, the firm-date combination in random simulations discussed above is constructed by a firm portfolio with very few limitations on the fitness to M&A target firms. Thus, if we intend to have a better understanding of the unconditional scenario constructed only by M&A target firms, a simulation using target firms combined with random calendar days will be of interest. On the other hand, a subsample exclude firms that become targets within the successive year of the pseudo event day could be used to

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[5]The 4^{th} merger wave is from 1981 to 1989; the 5^{th} merger wave is from 1994 to 2001. During these two decades, there are two recessions, early 1980s recession (1980 – 1982) and dot-com recession (2002 and 2003 in the United States).

Table 9. Regression Results of M&A Sample Comparison Between Three Studies

	This Paper	Schwert (1996)	Betton, Eckbo &Thorburn (2008)
Sample Time Period	1990-2012	1975-1991	1980-2002
Stock Exchange	NYSE, AMEX, NASDAQ	NYSE, AMEX	All US publicly traded Targets
Sample Size	4366	1814	7522
Regression Model	$\text{Markup}_i = a + b\,\text{Runup}_i + u_i$	$\text{Premium}_i = a + b\,\text{Runup}_i + u_i$	$\text{Markup}_i = a + b\,\text{Runup}_i + e_i$
Intercept	0.1913	0.0840	-0.0660
	(29.4757***)	(8.3400***)	(-6.9900***)
CAR [-42,-1]	0.1753	0.1300[6]	0.5950
	(for b=0, 6.8376***)	(for b=1, 2.88**)	(for b=1, 71.33***), (for b=0, 26.64***)

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]; Mark-ups are estimated over day [0, +126 or delisting day];
The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

Table 10. Different Exchange Group Regression Results

Pure Random represent regression coefficients from simulation sample, which average coefficients across 10,000 runs. ***% T Sig.*** shows percentage of t-statistics derived from regression in each run that are significant at 5% level. ***T-stat (H0: Mu=0)*** displays results of t-test examining with null hypothesis *H0: Mu=0.* Note that population std. deviation is used while calculating ***T-stat (H_0: Mu=0)***, simply times them by $\sqrt{N}$=100 to get t-stats using sample std. deviation. ***T-stat (H0: $Mu_{NYSE\&AMEX}$=Mu_{NASDAQ})*** presents results from two-sample t-test with a null hypothesis that there is no significant difference between coefficient mean in NYSE&AMEX sample and that in NASDAQ sample.

	N	Pure Random	% T Sig.	T-stat (H0: Mu=0)	T-stat (H_0: $Mu_{NYSE\&AMEX}$=Mu_{NASDAQ})	Obs at 5th Percentile	Obs at 95th Percentile
					NYSE & AMEX		
Intercept	10000	0.0986				0.0183	0.1782
		(2.4180)	65.40	(2.04*)	(-91.23***)		
CAR [-42,-1]	10000	0.4170				0.3128	0.522
		(13.6512)	100	(6.43***)	(-20.89***)		
Size	10000	-0.0092				-0.0140	-0.0042
		(-3.2695)	89.02	(-3.07**)	(32.49***)		
Industry	10000	0.0001				-0.000	0.0000
		(0.5017)	11.50	(0.44)	(-0.83)		
					NASDAQ		
Intercept	10000	0.3385				0.2293	0.4485
		(5.1786)	99.97	(5.07***)	n/a		
CAR [-42,-1]	10000	0.4723				0.3724	0.5856
		(15.1600)	100	(7.17***)	n/a		
Size	10000	-0.0325				-0.041	-0.0241
		(-6.2350)	89.12	(-6.33***)	n/a		
Industry	10000	0.0003				-0.0000	0.0000
		(0.6466)	11.29	(0.61)	n/a		

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]; Mark-ups are estimated over day [0, +126 or delisting day];
The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

[6] Schwert (1996) got 1.13 using the model cited in his study, 0.13 is the b estimate after adjustment via Equation (4) cited in Section 5 of this paper.

testify the run-up and mark-up relation under a scenario without M&A event effects. However, due to the small fraction of real M&A target-date combinations (4,171 real M&A target-date combinations out of 46,718,352 firm-date combinations in the simulation pool), the change of the estimated relation between run-ups and mark-ups is expected to be negligible. Therefore, the subsample of random target-date combinations will be the choice of my investigation to further study the new baseline of relation between run-ups and mark-ups.

The subsample is constructed by combining target firm in M&A sample and all the calendar day between Jan 1st 1990 to Dec 31st 2012 one by one. With 4,171 target firms and 8,401 calendar days, the random target-date portfolio includes 35,040,571 observations. Pure random simulation and time stratified random simulation approaches have been conducted using this portfolio, resulting in 2 simulation subsamples with 10,000 runs (follow the same approach in Section 3.2). Since this subsample uses real target firms and contains M&A event effects, I expect the estimated relation of interest to be reduced if the new baseline established in the previous sections is robust. Additionally, the b estimate in time stratified random simulation should be even smaller as this subsample includes more time concentration effect of M&A deals.

Single-factor and multiple regressions have be conducted for both simulation subsamples. Regression results are displayed in Table 11. As expected, the results have shown a good agreement with my previous findings, indicating substitution hypothesis might outweigh mark-up pricing hypothesis. That is to say, the average b estimate decreases to a significant 0.45 for pure random simulation sample (0.43 for time stratified random simulation sample) under both single-factor and multiple regressions. This reduced b coefficient is consistent with my expectation that the relation between real run-ups and mark-ups are smaller in magnitude than that between two random CARs under the normal scenario.

Moreover, we could observe from Table 12 that even b estimate at the 1st percentile of the empirical distribution (derived from the four subsamples) is much larger than that of M&A sample, which makes my previous conclusion more plausible.

Table 11. Regression Results for Target Firm with Random Date Simulation

% T Sig. shows percentage of t-statistics derived from regression in each run that are significant at 5% level. ***T-stat (H0: Mu=0)*** displays results of t-test examining with null hypothesis *H0: Mu=0*. Note that population std. deviation is used while calculating ***T-stat (H_0: Mu=0)***, simply times them by $\sqrt{N}$=100 to get t-stats using sample std. deviation.

	N	Pure Random Simulation	% T Sig.	T-stat (H0: Mu=0)	Time Stratified Random Simulation	% T Sig.	T-stat (H0: Mu=0)
				Single Factor			
Intercept	10000	-0.0003			0.0076		
		(-0.0452)	4.6	(-0.0434)	(1.1008)	19.31	(1.1127)
CAR [-42,-1]	10000	0.4520			0.4304		
		(14.9758)	100	(9.5313***)	(14.2711)	100	(8.9803***)
				Multiple Regression			
Intercept	10000	0.0107			0.0125		
		(0.1824)	5.24	(0.1817)	(0.2098)	6.1	(0.2064)
CAR [-42,-1]	10000	0.4521			0.4304		
		(14.9724)	100	(9.5296***)	(14.2657)	100	(8.9758***)
Size	10000	-0.0009			-0.0001		
		(-0.2072)	5.31	(-0.2100)	(-0.0302)	4.98	(-0.0311)
Stock Exchange	10000	0.0007			-0.0046		
		(0.0426)	4.7	(0.0428)	(-0.2790)	4.87	(-0.2898)
Industry	10000	0.0000			0.0000		
		(0.0303)	6.6	(0.0291)	(-0.0784)	6.46	(-0.0735)

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

Table 12. b Estimates Distribution at Different Percentiles (Target-Random Date Subsample)

	Single Factor Regression		Multiple Regression	
Percentile	Pure Random	Time Stratified	Pure Random	Time Stratified
1	0.3393	0.3189	0.3394	0.3190
5	0.3739	0.3512	0.3740	0.3511
10	0.3917	0.3694	0.3918	0.3694
25	0.4205	0.3983	0.4205	0.3983
50	0.4522	0.4306	0.4523	0.4305
75	0.4838	0.4624	0.4839	0.4624
90	0.5128	0.4922	0.5131	0.4923
95	0.5304	0.5078	0.5303	0.5080
99	0.5603	0.5411	0.5607	0.5413
100	0.6210	0.6147	0.6203	0.6146

However, due to the inadequate empirical tests and the dispersions with previous studies, it is not clear which hypothesis gains more support for sure. In fact, the development of the two hypotheses could have certain constrains, for instance, improper expectation of the b estimate range as [-1, 0]. Facing an empirical b estimate of 0.46 under the normal scenario and a b estimate of 0.45 under target firm normal scenario, it is critical to reconsider the design of the hypothesis itself.

Interpretation of the finding that the run-up and mark-up relation is higher under normal scenario than that under M&A scenario could be the return reversal after the M&A announcement. As target stock price usually soars short before and on the announcement day, and drops back to a level where we could only have a slightly positive excess return (which is rather small in magnitude), real target run-ups and mark-ups tend to show a weaker positive relationship instead of a strong positive relation between two simulation CARs under the normal scenario, which is likely caused by the momentum effect in stock price.

To sum up, although we have drawn valuable inferences from the empirical b estimates in random simulation regressions, the conclusion still remains open for future discussion.

6. Robustness test

Since this study investigates relation between successive abnormal returns for a certain firm, serial correlation is the first problem that we should bring to the table. Hence, following Betton et al. (Betton, Eckbo, Thompson, & Thorburn, 2014), serial correlation test is conducted by first sorting the dataset according to the magnitude of run-ups, then complete Durbin-Watson (Durbin & Watson, 1950) test for residuals of the regression.

I choose the 5000th run from each simulations as the testing samples, namely pure random single-factor sample, pure random multiple sample, time stratified random single-factor sample and time stratified random multiple sample. Similarly, White test for heteroscadastisity (White, 1980) and Variance Inflation Factor (VIF) are examined for each testing sample where applicable.

According to the results in Table 14 (in Appendix), Durbin-Watson estimates are very close to two with p-values larger than 0.1, thus there is no strong evidence for serial correlation; VIF value around 1.0 in multiple regression indicates a fair performance as related to multicolinearity issue. Nevertheless, both single-factor and multiple regression models have variables that fail to pass White Test for heteroskedasticity. Therefore, the only issue that we should pay attention to is the heteroskedasticity problem which involves in OLS regression model for both M&A and simulation samples.

To resolve this problem, weighted least square regressions have been conducted for both simulation samples (pure random and time stratified random) and M&A sample using single factor model (Equation 4) in Section 5.1. Not surprisingly, after correcting heteroskedasticity problem, the magnitude of b estimates for all three samples has slightly decreased. This slight decrease, however, does not cause any substantial change for discussions in previous sections. Detailed results of the WLS regression can be found in Table 15 in the Appendix.

It is consistent with the conclusion that, during the M&A process, substitution hypothesis tends to overweigh mark-up pricing hypothesis, and the conclusion is still open for further discussion. If substitution hypothesis gains the upper hand, it will provide more support for the rational two-party bargaining scenario where there are more private information involved in the decision of both sides than that have been reflected in the open market. More specifically, it consists with the semi-strong form efficient market hypothesis, suggesting that the market price reflects all the public information and the two parties are therefore confidently playing with their private information regardless of the run-ups in target stock price.

7. Conclusion

Following previous studies on relation between target pre-bid run-ups and post-bid mark-ups, this paper examine that relation under the normal scenario using large sample simulations. Sampled firms are exchange-listed in NYSE, AMEX and NASDAQ over a period of 1990 to 2012. Cross-sectional event study has been conducted for each combination of random selected date and sampled firm. Simulation methods include simple random selection and time stratified random selection which assigns different weights to each time period according to the real M&A concentration over time.

Interested in answering the question of how big the pre-bid run-ups are, I study the empirical distribution of run-ups from the simulation samples. As comparing to a pre-bid CAR of -0.3463 at 5^{th} percentile (i.e. -0.3555 for time stratified simulation) and 0.3172 at 95^{th} percentile (i.e. 0.3266 for time stratified simulation) from the empirical run-up distribution, only 13% of M&A run-ups in this study could be recognized as abnormal at 10% significance level. The usage of empirical simulation run-up distribution as a new benchmark casts doubts on the traditional way to distinguish whether pre-bid run-ups are of great importance.

While examining the relation between run-ups and mark-ups via OLS regression model, an unexpected b coefficient using simulation sample has been reported by the results. An average b coefficient of 0.46 contradicts the hypothesized range of [-1, 0] for this coefficient, and then establishes a reasonable baseline to test substitution/mark-up pricing hypothesis. To be more specific, we expect a b coefficient that is larger than the baseline of 0.46 under mark-up pricing hypothesis and vice versa. Contrary to Schwert (1996), it is believed that his findings, as well as findings in this paper, provide more support to substitution hypothesis, the design of the two competing hypotheses are in need of modification though. This finding shows an agreement with the momentum effect documented in the literature, and the reversal of target stock price after M&A announcement could also be a possible explanation for the weaker relationship between real M&A pre-bid run-ups and post-bid mark-ups.

To summarize, in order to better understand pre-bid run-ups and the relation between run-ups and mark-ups, this study provides valuable inferences drawn from empirical investigation under a normal scenario via large sample simulation. Nevertheless, there are certain limitations involved: 1) empirical tests are in need to further examine findings in this paper, and 2) it is possible that the research methodology applied in this paper causes certain impacts on the study results. Therefore, future study is in need to further testify the findings cited in this paper and to achieve a sound conclusion for our discussion.

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Appendix

Table 13. Time Weight Across M&A Sample Period

Year	Count	%
1990	14	0.34%
1991	19	0.46%
1992	28	0.67%
1993	52	1.25%
1994	115	2.76%
1995	151	3.62%
1996	193	4.63%
1997	276	6.62%
1998	318	7.62%
1999	428	10.26%
2000	330	7.91%
2001	235	5.63%
2002	143	3.43%
2003	164	3.93%
2004	191	4.58%
2005	212	5.08%
2006	258	6.19%
2007	288	6.90%
2008	167	4.00%
2009	101	2.42%
2010	172	4.12%
2011	165	3.96%
2012	151	3.62%
Total	4171	100.00%

Table 14. Diagnostic Tests for Regression Model

	Heteroscedasticity		Serial Correlation			Multicolinearity
	White Test	Durbin-Watson D	Pr<DW	Pr>DW	1st Order Autocorrelation	VIF
			M&A Sample Single Factor Regression			
Intercept	<.0001	2.0330	0.8564	0.1436	-0.0170	N/A
CAR [-42,-1]	<.0001					N/A
			M&A Sample Multiple Regression			
Intercept	<.0001	1.982	0.2789	0.7211	0.009	0.0000
CAR [-42,-1]	<.0001					1.0173
Size	<.0001					1.3520
Stock Exchange	0.4304					1.3357
Industry	0.0022					1.0126
			5000th Pure Random Sample Single Factor Regression			
Intercept	<.0001	1.9800	0.2512	0.7488	0.0080	N/A
CAR [-42,-1]	<.0001					N/A
			5000th Time Stratified Random Sample Single Factor Regression			
Intercept	0.0420	1.9860	0.3151	0.6849	-0.0020	N/A
CAR [-42,-1]	<.0001					N/A
			5000th Pure Random Sample Multiple Regression			
Intercept	0.0030	2.011	0.6413	0.3587	-0.0060	0.0000
CAR [-42,-1]	<.0001					1.0032
Size	<.0001					1.1204
Stock Exchange	0.0040					1.1145
Industry	0.7680					1.0033
			5000th Time Stratified Random Sample Multiple Regression			
Intercept	<.0001	1.9860	0.3164	0.6836	-0.0020	0.0000
CAR [-42,-1]	<.0001					1.0038
Size	<.0001					1.1455
Stock Exchange	0.0106					1.1378
Industry	0.8911					1.0057

Table 15. Single Factor WLS Regression Results

	N	Pure Random (5000th run)	Obs at 5th Percentile	Obs at 95th Percentile	Time Stratified Random (5000th run)	Obs at 5th Percentile	Obs at 95th Percentile
				Simulation Runs			
Intercept	10000	-0.0068	-0.0130	-0.0013	-4.4426	-0.0142	-0.0022
		(-2.4034*)	(-4.4426***)	(-0.5399)	(-2.7226**)	(-4.6912***)	(-0.9408)
CAR [-42,-1]	10000	0.3229	0.2337	0.4070	0.3356	0.2496	0.4200
		(10.8088***)	(7.7647***)	(13.5106***)	(10.8907***)	(8.0334***)	(13.4952***)
				M&A Sample			
Intercept	4171	0.1696	n/a	n/a			
		(35.4131***)					
CAR [-42,-1]	4171	0.0695	n/a	n/a			
		(2.4979*)					

T Test for Null Hypothesis: Mu0=0

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test.

Table 16 Pseudo vs. Real Target Pre-bid Run-ups at All Percentiles

M&A*, *Pure Random, and ***Time Stratified Random*** list the CARs from each sample at 100 percentiles. ***T-stat (H_0: M&A CAR=0)*** displays the t-statistics for t-test with null hypothesis of $H_0: CAR_{M\&A} = 0$ for M&A CAR at each percentile. ***vs 5th (95th) Percentile of Simulation*** compares M&A CAR at selected percentile with average simulation CAR at 5th (95th) percentile if M&A CAR has a negative sign (positive sign). ***<% 5th or > % 95th Pure Random*** denotes the proportion of 10,000 simulation CARs at 5th percentile that are larger than M&A CAR at selected percentile, or proportion of 10,000 simulation CARs at 95th percentile that are smaller than M&A CAR at selected percentile. ***T-stat (H0: Simu 5th (95th) > M&A)*** denotes the t-statistics from t-tests with null hypothesis of $H_0: average\ 5^{th}(95^{th})CAR_{simu} > CAR_{M\&A}$, where $CAR_{M\&A} < 0$ $(CAR_{M\&A} > 0)$, standard deviation used for tests involving with average simulation 5th CAR is $\sigma = \sqrt{\frac{1}{10{,}000}\sum_{i=1}^{10{,}000}(Simu\ Pct5_i - \mu)^2}$, where $\mu = \frac{1}{10{,}000}\sum_{i=1}^{10{,}000} Simu\ Pct5_i$. Same formula applies when calculating standard deviation used for tests with average simulation 95th CAR. Note that population std. deviation is used while calculating ***T-stat (H_0: Simu 5th (95th) > M&A)***, simply times them by $\sqrt{N}$=100 to get t-stats using sample std. deviation

PCTL	M&A	T-stat (H0: M&A CAR=0)	Pure Random	vs 5th (95th) Percentile of Simulation	<% 5th or > % 95th Pure Random	T-stat (H_0: Simu 5th (95th) > M&A)	Time Stratified Random	vs 5th (95th) Percentile of Simulation	<% 5th or > % 95th Time Random	T-stat (H_0: Simu 5th (95th) >M&A)
pct1	-0.5360	-142.96***	-0.6436	<	100.00	***6.4036****	-0.6661	<	100.00	***5.6624****
pct2	-0.4315	-115.08***	-0.5098	<	63.33	***4.2944****	-0.5260	<	100.00	***3.6386****
pct3	-0.3499	-93.33***	-0.4366	<	0.37	0.2324	-0.4485	>	32.24	-0.3371
pct4	-0.2983	-79.57***	-0.3851	>	0.00	-3.7138	-0.3960	>	0.00	-4.0886
pct5	-0.2633	-70.24***	-0.3463	>	0.00	-7.4409	-0.3555	>	0.00	-7.7163
pct6	-0.2367	-63.13***	-0.3162	>	0.00	-11.0993	-0.3235	>	0.00	-11.2451
pct7	-0.2179	-58.12***	-0.2906	>	0.00	-14.4189	-0.2976	>	0.00	-14.3557
pct8	-0.1986	-52.96***	-0.2689	>	0.00	-18.2104	-0.2751	>	0.00	-17.9524
pct9	-0.1851	-49.38***	-0.2505	>	0.00	-21.3523	-0.2556	>	0.00	-21.1415
pct10	-0.1710	-45.60***	-0.2338	>	0.00	-25.0097	-0.2384	>	0.00	-24.8557
pct11	-0.1582	-42.20***	-0.2190	>	0.00	-28.6822	-0.2234	>	0.00	-28.3140
pct12	-0.1452	-38.72***	-0.2059	>	0.00	-32.6118	-0.2096	>	0.00	-31.9738
pct13	-0.1323	-35.28***	-0.1936	>	0.00	-36.6321	-0.1970	>	0.00	-35.9337
pct14	-0.1220	-32.55***	-0.1825	>	0.00	-40.4740	-0.1858	>	0.00	-39.6353
pct15	-0.1152	-30.72***	-0.1724	>	0.00	-43.6751	-0.1751	>	0.00	-43.1712

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test.

PCTL	M&A	T-stat (H0: M&A CAR=0)	Pure Random	vs 5^{th} (95^{th}) Percentile of Simulation	<% 5^{th} or > % 95^{th} Pure Random	T-stat (H_0: Simu 5^{th} (95^{th}) > M&A)	Time Stratified Random	vs 5^{th} (95^{th}) Percentile of Simulation	<% 5^{th} or > % 95^{th} Pure Random	T-stat (H_0: Simu 5^{th} (95^{th}) > M&A)
pct16	-0.1048	-27.96***	-0.1629	>	0.00	-47.7912	-0.1653	>	0.00	-47.4127
pct17	-0.0981	-26.18***	-0.1541	>	0.00	-51.4031	-0.1563	>	0.00	-51.2531
pct18	-0.0923	-24.61***	-0.1460	>	0.00	-55.1661	-0.1480	>	0.00	-54.9236
pct19	-0.0863	-23.01***	-0.1382	>	0.00	-58.9068	-0.1400	>	0.00	-58.6080
pct20	-0.0804	-21.44***	-0.1309	>	0.00	-62.4764	-0.1325	>	0.00	-62.0427
pct21	-0.0740	-19.74***	-0.1242	>	0.00	-66.2287	-0.1256	>	0.00	-65.5589
pct22	-0.0681	-18.17***	-0.1176	>	0.00	-70.5447	-0.1190	>	0.00	-69.7203
pct23	-0.0636	-16.97***	-0.1114	>	0.00	-74.4637	-0.1126	>	0.00	-73.6528
pct24	-0.0575	-15.32***	-0.1056	>	0.00	-78.5429	-0.1066	>	0.00	-77.6079
pct25	-0.0537	-14.32***	-0.1000	>	0.00	-82.4102	-0.1010	>	0.00	-81.2900
pct26	-0.0489	-13.03***	-0.0946	>	0.00	-86.3954	-0.0955	>	0.00	-85.3191
pct27	-0.0430	-11.47***	-0.0896	>	0.00	-90.6725	-0.0903	>	0.00	-89.5477
pct28	-0.0385	-10.27***	-0.0847	>	0.00	-95.0526	-0.0854	>	0.00	-93.5136
pct29	-0.0342	-9.13***	-0.0799	>	0.00	-99.2219	-0.0805	>	0.00	-97.8531
pct30	-0.0293	-7.81***	-0.0754	>	0.00	-102.8317	-0.0759	>	0.00	-102.2696
pct31	-0.0256	-6.83***	-0.0710	<	0.00	-106.7527	-0.0714	>	0.00	-106.4791
pct32	-0.0211	-5.62***	-0.0667	<	0.00	-111.0701	-0.0672	>	0.00	-110.4302
pct33	-0.0164	-4.39***	-0.0627	<	0.00	-115.5017	-0.0630	>	0.00	-115.1530
pct34	-0.0130	-3.47***	-0.0587	<	0.00	-119.8096	-0.0590	>	0.00	-119.0158
pct35	-0.0088	-2.34*	-0.0548	<	0.00	-124.3332	-0.0552	>	0.00	-123.2741
pct36	-0.0054	-1.45	-0.0511	<	0.00	-128.0818	-0.0514	>	0.00	-127.0464
pct37	-0.0011	-0.30	-0.0475	<	0.00	-132.2498	-0.0477	>	0.00	-131.1365
pct38	0.0034	0.91	-0.0439	<	0.00	-136.7123	-0.0441	<	0.00	-134.9314
pct39	0.0060	1.59	-0.0405	<	0.00	-141.1300	-0.0406	<	0.00	-139.0221
pct40	0.0088	2.34*	-0.0371	<	0.00	125.3989	-0.0372	<	0.00	124.3009

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test.

PCTL	M&A	T-stat (H0: M&A CAR=0)	Pure Random	vs 5^{th} (95^{th}) Percentile of Simulation	<% 5^{th} or > % 95^{th} Pure Random	T-stat (H_0: Simu 5^{th} (95^{th}) > M&A)	Time Stratified Random	vs 5^{th} (95^{th}) Percentile of Simulation	<% 5^{th} or > % 95^{th} Pure Random	T-stat (H_0: Simu 5^{th} (95^{th}) > M&A)
pct41	0.0138	3.69***	-0.0337	<	0.00	125.6515	-0.0338	<	0.00	125.0600
pct42	0.0171	4.55***	-0.0305	<	0.00	127.1296	-0.0306	<	0.00	126.1017
pct43	0.0218	5.82***	-0.0273	<	0.00	127.8305	-0.0274	<	0.00	126.5033
pct44	0.0258	6.88***	-0.0242	<	0.00	127.9799	-0.0243	<	0.00	127.1626
pct45	0.0297	7.92***	-0.0212	<	0.00	128.1632	-0.0213	<	0.00	127.5256
pct46	0.0342	9.12***	-0.0182	<	0.00	128.0776	-0.0183	<	0.00	128.0169
pct47	0.0383	10.21***	-0.0153	<	0.00	128.7231	-0.0153	<	0.00	128.8592
pct48	0.0426	11.36***	-0.0124	<	0.00	128.6751	-0.0124	<	0.00	128.8491
pct49	0.0469	12.50***	-0.0096	<	0.00	128.5172	-0.0096	<	0.00	129.0515
pct50	0.0505	13.48***	-0.0069	<	0.00	128.6262	-0.0068	<	0.00	129.4243
pct51	0.0541	14.43***	-0.0041	<	0.00	128.9783	-0.0040	<	0.00	129.8475
pct52	0.0582	15.52***	-0.0014	<	0.00	128.6189	-0.0014	<	0.00	129.4623
pct53	0.0617	16.45***	0.0013	<	0.00	126.7519	0.0014	<	0.00	127.9080
pct54	0.0670	17.88***	0.0040	<	0.00	122.8006	0.0041	<	0.00	124.1996
pct55	0.0713	19.02***	0.0068	<	0.00	119.2104	0.0069	<	0.00	120.7557
pct56	0.0753	20.08***	0.0095	<	0.00	116.0755	0.0096	<	0.00	116.8415
pct57	0.0805	21.46***	0.0123	<	0.00	112.1548	0.0125	<	0.00	112.7503
pct58	0.0845	22.53***	0.0152	<	0.00	108.2549	0.0154	<	0.00	109.4499
pct59	0.0899	23.97***	0.0181	<	0.00	104.5191	0.0183	<	0.00	105.4382
pct60	0.0951	25.35***	0.0211	<	0.00	100.3534	0.0213	<	0.00	101.2549
pct61	0.0991	26.44***	0.0241	<	0.00	96.7865	0.0244	<	0.00	97.6273
pct62	0.1041	27.77***	0.0272	<	0.00	92.8270	0.0276	<	0.00	93.7617
pct63	0.1084	28.91***	0.0304	<	0.00	89.3105	0.0307	<	0.00	89.9130
pct64	0.1139	30.37***	0.0337	<	0.00	84.7889	0.0341	<	0.00	85.5269
pct65	0.1202	32.05***	0.0370	<	0.00	80.0183	0.0376	<	0.00	81.0345

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test

PCTL	M&A	T-stat (H0: M&A CAR=0)	Pure Random	vs 5th (95th) Percentile of Simulation	<% 5th or > % 95th Pure Random	T-stat (H_0: Simu 5th (95th) > M&A)	Time Stratified Random	vs 5th (95th) Percentile of Simulation	<% 5th or > % 95th Pure Random	T-stat (H_0: Simu 5th (95th) > M&A)
pct66	0.1249	33.33***	0.0406	<	0.00	76.3282	0.0410	<	0.00	77.1231
pct67	0.1313	35.02***	0.0442	<	0.00	71.8593	0.0447	<	0.00	72.8219
pct68	0.1363	36.37***	0.0479	<	0.00	68.1647	0.0486	<	0.00	68.8516
pct69	0.1424	37.99***	0.0518	<	0.00	64.1033	0.0525	<	0.00	64.6572
pct70	0.1492	39.81***	0.0558	<	0.00	59.5741	0.0566	<	0.00	60.2363
pct71	0.1574	41.97***	0.0599	<	0.00	55.0447	0.0609	<	0.00	55.5989
pct72	0.1652	44.07***	0.0643	<	0.00	50.5782	0.0654	<	0.00	51.4276
pct73	0.1726	46.04***	0.0689	<	0.00	46.7873	0.0699	<	0.00	47.5751
pct74	0.1788	47.69***	0.0736	<	0.00	43.4874	0.0748	<	0.00	43.9894
pct75	0.1866	49.77***	0.0786	<	0.00	39.6067	0.0800	<	0.00	40.2725
pct76	0.1943	51.81***	0.0839	<	0.00	35.9654	0.0852	<	0.00	36.7388
pct77	0.2011	53.64***	0.0893	<	0.00	32.7748	0.0909	<	0.00	33.6409
pct78	0.2111	56.31***	0.0951	<	0.00	28.9763	0.0968	<	0.00	29.8827
pct79	0.2207	58.86***	0.1013	<	0.00	25.3666	0.1031	<	0.00	26.2899
pct80	0.2302	61.41***	0.1076	<	0.00	21.9150	0.1096	<	0.00	23.0128
pct81	0.2384	63.59***	0.1145	<	0.00	19.0270	0.1167	<	0.00	20.1727
pct82	0.2476	66.05***	0.1219	<	0.00	16.0680	0.1243	<	0.00	17.2840
pct83	0.2593	69.17***	0.1296	<	0.00	12.7375	0.1322	<	0.00	14.0250
pct84	0.2687	71.68***	0.1380	<	0.00	10.1940	0.1408	<	0.00	11.5307
pct85	0.2802	74.74***	0.1471	<	0.01	7.3842	0.1501	<	0.00	8.7748
pct86	0.2942	78.48***	0.1567	<	1.76	4.3416	0.1603	<	0.00	5.7767
pct87	0.3085	82.29***	0.1674	<	22.14	1.5494	0.1710	<	0.21	3.0655
pct88	0.3201	85.38***	0.1791	>	60.82	-0.4881	0.1831	<	5.88	1.0354
pct89	0.3371	89.92***	0.1918	>	95.88	***-3.1205****	0.1965	>	29.64	-1.5541
pct90	0.3525	94.01***	0.2062	>	99.87	***-5.1668*****	0.2111	>	81.49	***-3.5608*****

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]
The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test

PCTL	M&A	T-stat (H0: M&A CAR=0)	Pure Random	vs 5^{th} (95^{th}) Percentile of Simulation	<% 5^{th} or > % 95^{th} Pure Random	T-stat (H_0: Simu 5^{th} (95^{th}) > M&A)	Time Stratified Random	vs 5^{th} (95^{th}) Percentile of Simulation	<% 5^{th} or > % 95^{th} Pure Random	T-stat (H_0: Simu 5^{th} (95^{th}) > M&A)
pct91	0.3750	100.02***	0.2225	>	100.00	***-7.7886****	0.2278	>	98.55	***-6.1624****
pct92	0.4024	107.34***	0.2405	>	100.00	***-10.6327****	0.2470	>	99.99	***-8.9308****
pct93	0.4259	113.60***	0.2618	>	100.00	***-12.3362****	0.2691	>	100.00	***-10.6610****
pct94	0.4549	121.33***	0.2872	>	100.00	***-13.9277****	0.2947	>	100.00	***-12.3340****
pct95	0.4837	129.01***	0.3172	>	100.00	***-14.8066****	0.3266	>	100.00	***-13.3167****
pct96	0.5302	141.43***	0.3559	>	100.00	***-16.2447****	0.3669	>	100.00	***-14.7649****
pct97	0.5753	153.46***	0.4079	>	100.00	***-16.1813****	0.4197	>	100.00	***-14.7606****
pct98	0.6549	174.68***	0.4833	>	100.00	***-16.1437****	0.5007	>	100.00	***-14.6107****
pct99	0.7796	207.94***	0.6265	>	100.00	***-14.2537****	0.6523	>	100.00	***-12.9278****
pct100	2.2632	603.67***	2.2418	>	100.00	***-1.8344$***	2.4232	>	100.00	-1.6027

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1]

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test

Table 17 Standard Pseudo Target Pre-bid Run-ups at All Percentiles (across 10, 000 Runs)

PCTL	Std. M&A	Std. Pure Random	Difference	vs 5th (95th) Percentile of Simulation 1	Std. Time Stratified Random	vs 5th (95th) Percentile of Simulation 2
pct1	-1.7412	-2.1881	0.4469	<	-2.1378	<
pct2	-1.4016	-1.7330	0.3314	<	-1.6883	<
pct3	-1.1367	-1.4844	0.3477	>	-1.4395	>
pct4	-0.9692	-1.3090	0.3398	>	-1.2712	>
pct5	-0.8554	***-1.1773***	0.3219	>	***-1.1410***	>
pct6	-0.7688	-1.0749	0.3060	>	-1.0384	>
pct7	-0.7078	-0.9880	0.2802	>	-0.9552	>
pct8	-0.6450	-0.9141	0.2691	>	-0.8831	>
pct9	-0.6014	-0.8515	0.2501	>	-0.8204	>
pct10	-0.5554	-0.7949	0.2396	>	-0.7652	>
pct11	-0.5140	-0.7444	0.2304	>	-0.7171	>
pct12	-0.4716	-0.6999	0.2283	>	-0.6726	>
pct13	-0.4297	-0.6583	0.2286	>	-0.6323	>
pct14	-0.3965	-0.6203	0.2238	>	-0.5962	>
pct15	-0.3741	-0.5861	0.2120	>	-0.5621	>
pct16	-0.3406	-0.5538	0.2132	>	-0.5307	>
pct17	-0.3189	-0.5238	0.2049	>	-0.5015	>
pct18	-0.2998	-0.4963	0.1965	>	-0.4750	>
pct19	-0.2803	-0.4699	0.1896	>	-0.4494	>
pct20	-0.2611	-0.4451	0.1839	>	-0.4254	>
pct21	-0.2405	-0.4221	0.1816	>	-0.4033	>
pct22	-0.2212	-0.3998	0.1785	>	-0.3818	>
pct23	-0.2067	-0.3787	0.1720	>	-0.3615	>
pct24	-0.1866	-0.3591	0.1725	>	-0.3422	>
pct25	-0.1745	-0.3400	0.1655	>	-0.3242	>
pct26	-0.1588	-0.3218	0.1630	>	-0.3067	>
pct27	-0.1397	-0.3046	0.1649	>	-0.2898	>
pct28	-0.1251	-0.2878	0.1627	>	-0.2740	>
pct29	-0.1112	-0.2716	0.1604	>	-0.2585	>
pct30	-0.0952	-0.2564	0.1612	>	-0.2436	>
pct31	-0.1057	-0.2413	0.1356	>	-0.2293	>
pct32	-0.0870	-0.2268	0.1398	>	-0.2157	>
pct33	-0.0679	-0.2131	0.1452	>	-0.2023	>
pct34	-0.0537	-0.1995	0.1458	>	-0.1893	>
pct35	-0.0362	-0.1863	0.1502	>	-0.1771	>
pct36	-0.0224	-0.1738	0.1514	>	-0.1649	>
pct37	-0.0046	-0.1613	0.1567	>	-0.1530	>
pct38	0.0142	-0.1492	0.1633	<	-0.1417	<
pct39	0.0247	-0.1376	0.1623	<	-0.1304	<
pct40	0.0285	-0.1260	0.1545	<	-0.1194	<
pct41	0.0449	-0.1147	0.1596	<	-0.1086	<
pct42	0.0555	-0.1038	0.1593	<	-0.0983	<
pct43	0.0709	-0.0929	0.1638	<	-0.0880	<
pct44	0.0838	-0.0823	0.1662	<	-0.0780	<
pct45	0.0965	-0.0721	0.1686	<	-0.0683	<

PCTL	Std. M&A	Std. Pure Random	Difference	vs 5th (95th) Percentile of Simulation 1	Std. Time Stratified Random	vs 5th (95th) Percentile of Simulation 2
pct46	0.1111	-0.0619	0.1730	<	-0.0586	<
pct47	0.1243	-0.0519	0.1762	<	-0.0491	<
pct48	0.1383	-0.0423	0.1806	<	-0.0398	<
pct49	0.1522	-0.0326	0.1848	<	-0.0308	<
pct50	0.1642	-0.0233	0.1875	<	-0.0218	<
pct51	0.1758	-0.0139	0.1897	<	-0.0129	<
pct52	0.1890	-0.0046	0.1936	<	-0.0043	<
pct53	0.2004	0.0043	0.1960	<	0.0044	<
pct54	0.2178	0.0136	0.2041	<	0.0132	<
pct55	0.2316	0.0230	0.2086	<	0.0221	<
pct56	0.2445	0.0323	0.2122	<	0.0309	<
pct57	0.2614	0.0419	0.2194	<	0.0400	<
pct58	0.2743	0.0517	0.2226	<	0.0494	<
pct59	0.2919	0.0615	0.2305	<	0.0587	<
pct60	0.3088	0.0717	0.2371	<	0.0684	<
pct61	0.3220	0.0820	0.2400	<	0.0783	<
pct62	0.3383	0.0924	0.2458	<	0.0885	<
pct63	0.3521	0.1034	0.2487	<	0.0987	<
pct64	0.3699	0.1146	0.2554	<	0.1094	<
pct65	0.3904	0.1259	0.2645	<	0.1205	<
pct66	0.4059	0.1379	0.2680	<	0.1318	<
pct67	0.4265	0.1503	0.2763	<	0.1436	<
pct68	0.4429	0.1627	0.2802	<	0.1559	<
pct69	0.4626	0.1760	0.2866	<	0.1684	<
pct70	0.4848	0.1898	0.2951	<	0.1817	<
pct71	0.5112	0.2038	0.3074	<	0.1954	<
pct72	0.5368	0.2187	0.3181	<	0.2098	<
pct73	0.5607	0.2343	0.3264	<	0.2245	<
pct74	0.5808	0.2502	0.3306	<	0.2402	<
pct75	0.6062	0.2673	0.3389	<	0.2567	<
pct76	0.6311	0.2852	0.3458	<	0.2735	<
pct77	0.6534	0.3036	0.3497	<	0.2917	<
pct78	0.6858	0.3234	0.3624	<	0.3108	<
pct79	0.7168	0.3443	0.3726	<	0.3310	<
pct80	0.7479	0.3659	0.3820	<	0.3519	<
pct81	0.7745	0.3894	0.3851	<	0.3746	<
pct82	0.8044	0.4144	0.3900	<	0.3989	<
pct83	0.8425	0.4405	0.4020	<	0.4242	<
pct84	0.8730	0.4692	0.4038	<	0.4520	<
pct85	0.9102	0.5000	0.4102	<	0.4819	<
pct86	0.9558	0.5326	0.4232	<	0.5144	<
pct87	1.0022	0.5690	0.4332	<	0.5489	<
pct88	1.0399	0.6089	0.4310	<	0.5877	<
pct89	1.0952	0.6520	0.4432	>	0.6307	>
pct90	1.1450	0.7010	0.4439	>	0.6774	>
pct91	1.2181	0.7563	0.4618	>	0.7313	>

PCTL	Std. M&A	Std. Pure Random	Difference	vs 5th (95th) Percentile of Simulation 1	Std. Time Stratified Random	vs 5th (95th) Percentile of Simulation 2
pct92	1.3074	0.8176	0.4898	>	0.7927	>
pct93	1.3835	0.8901	0.4935	>	0.8638	>
pct94	1.4778	0.9763	0.5015	>	0.9458	>
pct95	1.5712	***1.0784***	0.4929	>	***1.0484***	>
pct96	1.7225	1.2101	0.5124	>	1.1776	>
pct97	1.8690	1.3867	0.4823	>	1.3470	>
pct98	2.1275	1.6431	0.4843	>	1.6071	>
pct99	2.5326	2.1299	0.4027	>	2.0937	>
pct100	7.3523	7.6212	-0.2689	>	7.7777	>

Run-ups are estimated over an estimation window of day [-297, -43], and an event window of day [-42,-1];

Difference denotes the difference between Std. M&A and Std. Pure Random.