"Stock liquidity, firm size and return persistence around mergers and acquisitions announcement"

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STOCK LIQUIDITY, FIRM SIZE AND RETURN PERSISTENCE AROUND MERGERS AND ACQUISITIONS ANNOUNCEMENT

Abstract

The paper examines market liquidity and size of 396 US firms engaged in mergers and acquisitions (M&A). The announcement-period returns are estimated using Carhart's four-factor model and estimated using two regression specifications. The results suggest that the return continuation depends on the degree of liquidity and the firm size. The positive and significant cumulative abnormal returns (CARs) under both the specifications with exception to the acquiring firms are found. Under the generalized autoregressive conditional heteroskedasticity (GARCH) model due to Glosten et al. (1993), hereafter, GJR-GARCH, the pre-event CARs are significant and persistent in contrast to the estimation based on the ordinary least squares (OLS) regression. This suggests possible leakage of information prior to an event announcement and further lends support to the contract theory of information asymmetry and signalling. It is also found that the target firms exhibit positive and significant post-event CARs for the mid-cap stocks. Whereas, for the acquirer firms, the post-event CARs for the small trading volume stocks are positive and significant. The results are robust to bootstrapping simulations.

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INTRODUCTION

Different theories are advanced to explain whether mergers and acquisitions (M&A) lead to predictable changes in the stock prices. The efficient market hypothesis (EMH) proposes that the price of a security fully and fairly reflects all available and relevant information. Therefore, the price will change only when new information is released (Mueller & Sirower, 2003). Therefore, if the stock market is assumed to be efficient, then the asset prices reflect the underlying true value of a company. In this paper, we examine the impact of stock liquidity and firm size on both target and acquiring firm liquidity. To what extent do mergers and acquisitions influence the stock liquidity? Liquidity is an elusive concept that has a lot of implications in the financial market. Prior empirical studies use several measures to capture liquidity factors that affect the magnitude of the stock returns. Empirical studies have focused on the liquidity and expected stock returns in relation to verifying the extent to which liquidity can affect ARs. As noted by Brunnermeier (2008), the 2008 financial crisis has large repercussions on the real economy and the "stock market capitalization of the major banks declined by more than twice as much". Corporate restructuring, such as mergers and acquisitions, are key examples of how important liquidity is in the investment climate.

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We evaluate the impact of stock market liquidity on mergers and acquisitions and the size of the firm. Given the virtual absence of documented market capitalization and trading volume as a measure of liquidity and the size of the firm, we felt there was the need to use them to test the impact of the stock returns on possible effects for shareholders. Ascioglu et al. (2002) find that both the trading volume and positive returns of target firms are higher before merger announcements and that after the announcements mostly large liquidity traders operate in the market leading to decline in stock returns. Nielsson (2009) suggested that if the trading volume of a particular stock is low, then the bid-ask spread is typically high, which makes the stock less liquid. Roosenboom et al. (2013) test whether stock liquidity affects acquirer returns and find that stock with lower liquidity has greater acquirer returns for acquisitions of unlisted acquired, relative to listed acquired.

Despite their empirical success, however, these studies did not use both market capitalization value and trading volume, concern with mergers and acquisitions, and consequently are unable to directly analyze the impact of stock liquidity on mergers and acquisitions. To date, there is no empirical research on both market capitalization and trading volume as a measure of stock liquidity on mergers and acquisitions. Thus, to our knowledge, an analysis of stock liquidity on target and acquiring firms and its relations, if any, with mergers and acquisitions has not yet been explored. This has motivated us to undertake this study using data on US firms and to test the result with robust methodology and efficient estimation method. The present study attempts to fill this apparent lack in the mergers and acquisitions literature.

Our contributions that this study makes to the mergers and acquisitions literature are discussed in detail here. First, we investigate the impacts of stock liquidity, measured by market capitalization value and trading volume on the magnitude of CARs for stocks that are associated with mergers and acquisitions. We are not aware of any US mergers and acquisitions study that has used both market capitalization and trading volume value as a measure of stock liquidity, grouping them into small, medium and large stocks. Second, prior studies rely on the magnitude of the ARs to provide evidence regarding the amount of gain or loss to shareholders around the announcement dates. To rely on such estimates, one has to assume that the CAPM used to estimate the ARs is correctly specified and that both the estimation method and the test for statistical significance are appropriate and reliable. Specifically, a test of whether shareholders gain around the merger announcement dates is a joint test that: i) the ARs are zero using a test statistic that is consistent with the return generating process, and ii) the CAPM used to generate the ARs is correctly specified. This means that the particular pricing model that is used needs to capture adequately the cross-sectional variation in stock returns. It is now generally acknowledged that augmenting the standard CAPM with the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor (hereafter, the F-F-C pricing factors) captures better the cross-sectional variation in returns relative to the basic CAPM[1]. This means that prior estimates of the ARs may not be sufficiently reliable and this, in turn, may lead to differences in the results of mergers and acquisitions studies. Thus, one of the aims of our paper is to estimate the ARs around merger announcements with a CAPM that is augmented with the F-F-C pricing factors, hereafter, the four-factor CAPM[2]. Third, we estimate the ARs using both the standard ordinary least square (OLS) regression and the generalized autoregressive conditional heteroskedasticity (GARCH) model due to Glosten et al. (1993), hereafter, GJR-GARCH model. We estimate the GJR-GARCH (1,1)-in-mean, i.e., GJR-GARCH-M, since we want to capture the volatility in the mean of the regression – often identified as a measure of risk tolerance in the literature. The OLS method does not perform well in the presence of heteroskedasticity even if

1 Indeed, the use of the F-F-C pricing factors tends to reduce or eliminate some of the mispricings that are not captured by the basic CAPM. Thus, Carhart (1997) shows that by including a momentum factor in the Fama and French (1993) three-factor CAPM, almost all the persistence in US mutual funds disappears. Fletcher and Forbes (2002) also find more or less similar results for UK unit trusts. We do not suggest that our four-factor CAPM is the only specification that works.

2 Draper and Paudyal (2006) use both the Fama-French three-factor and four-factor CAPM that includes momentum to capture the ARs around UK merger announcements. Similarly, Alexandridia et al. (2006) use the Fama-French three-factor CAPM to estimate the ARs for UK firms. Both studies estimate the ARs using the alpha/intercept from the regression of the CAPMs. Few US studies have estimated the ARs around merger announcements using the Fama-French-Carhart four-factor CAPM.

the parameter estimates are still unbiased[3]. The GJR-GARCH-M estimation method captures both the GARCH and asymmetry in both conditional mean and variance processes in the case of positive and negative stock return (Nam et al., 2002). In general, GARCH estimation methods lead to improvements in estimation efficiency (Engle, 2001). Specifically, we estimate the four-factor CAPM using both the standard OLS and GJR-GARCH-M (1,1)-in-mean estimation methods. We are not aware of any (other) merger and acquisitions study that estimates the four-factor CAPM using the GJR-GARCH-M estimation method[4]. In general, our study re-examines whether acquirers lose or gain nothing around merger announcements after allowing for both proper CAPM specification and estimation method. We also estimate the ARs under the OLS to determine where the ARs are over or underestimated relative to the GJR-GARCH-M estimation method. Finally, we test the statistical significance of our cumulative ARs (CARs) using Boehmer et al. (1991) (hereafter, BMP) *t*-statistic.

To summarize our results, on announcement day $t = 0$, US target firms generate positive and significant CARs following mergers and acquisitions under both specifications. Specifically, for target firms, under the GJR-GARCH-M method, the pre- and post-event CARs are positive and significant over eight-day event window t–2 to t+5. In contrast, the pre- and post-event CARs are positive and significant over six-day event window t–1 to t+4 under the OLS method. Thus, under the GJR-GARCH-M specification, the pre-event CARs are significant and persistent in contrast to the OLS estimate. This suggests possible leakage of information prior to an event announcement and further lends support to the contract theory of information asymmetry and signalling. On the announcement, the CARs for acquiring firms are positive and insignificant. The positive returns perceived during pre- and post-event and on announcement day $t = 0$, suggest that acquiring firms obtain synergies. Our results also show that there are no short-term negative CARs for US acquirers under the GJR-GARCH-M estimation method. Our CAR estimates are robust to bootstrapping simulation and, as such, we do not find that data snooping biases affect our results. Furthermore, we find a distinction between market capitalization value and trading volume to capture the impact of liquidity and the size of each firm on the magnitude of CARs for stocks that are associated with mergers and acquisitions. We find that the target firms exhibit positive and significant post-event CARs for the mid-cap stocks. Whereas, for the acquirer firms, the post-event CARs for the small trading volume stocks are positive and significant. This shows that the earlier the investor sells, the more he should expect to realize from the investment.

The paper is organized as follows: section 1 presents the literature reviews, section 2 presents the data set, section 3 describes the methodology, section 4 presents the bootstrapping simulation, section 5 describes the empirical results. The paper is concluded in the final section.

1. LITERATURE REVIEW

Liquidity is an elusive concept that has a lot of implications in the financial market. Many empirical studies use several measures to capture liquidity factors that affect the magnitude of the stock returns. Market liquidity affects the price of an asset. This means that for a particular asset, the higher it's market liquidity, the higher its price and the lower its expected return. These arguments suggest that large firms are more liquid and would, therefore, exhibit low expected returns. Likewise, small firms are less liquid and would generate high expected returns (Amihud, 2002). Portfolio theory suggests that investors who are risk-averse require higher expected return if the asset's market

3 The parameter estimates of the standard OLS are unbiased in the presence of non-normality as the estimates are the best linear unbiased estimate that can be achieved given that the OLS estimation method is linear. Even so, the use of residual correction methods such as the Newey-West method to correct for heteroscedasticity and auto-correction is not applicable in our case as we estimate the ARs using the regression residuals. Also, Chandra and Balachandran (1990) warn against the use of generalized least squares, especially in event studies, when that covariance matrix is known as this method is sensitive to model misspecification.

4 Whether or not prior studies estimate the ARs returns using the basic CAPM or four-factor CAPM, those studies do not estimate the model under the GJR-GARCH-M method. Also, while Draper and Puadyal (2006) and Alexandridis et al. (2006) estimate the three or four-factor CAPM, the abnormal returns are captured via the alpha or intercept term and using corrected standard errors for the alpha estimates. Balaban and Constantinou (2006) provide one of the few studies to estimate the ARs using symmetric GARCH.

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liquidity risk is greater. Empirical evidence suggests that broader bid-ask spreads of securities are linked with higher expected returns. Jones (2002) examines the stock market liquidity and trading costs on Dow Jones and NYSE stocks and finds that higher spreads predict high stock returns, whilst high turnover envisages low stock returns.

Chordia et al. (2001) examine patterns in market liquidity, trading activity, interest rates, default spreads, market returns and market volatility using NYSE listed stocks. They find that average daily changes in liquidity and trading activity are highly unpredictable and negatively serially dependent. Macroeconomic announcements such as GDP and unemployment rates also impact market liquidity. Market liquidity and trading activity are influenced by market returns, market volatility, and short- and long-term interest rates. They also indicate that liquidity drops and trading activity sluggish on Fridays.

2. DATA

To estimate the AR, we used daily stock price returns adjusted for dividends and stock splits for mergers and acquisitions announcements on NYSE, NASDAQ and AMEX for US firms from January 1, 2004 to December 31, 2014. The announcements were collected from Thompson Financial Reuters Database (electronic news source). The sample is selected based on the following considerations and the information should be obtained from Thompson Financial Reuters database: i) both the first public announcement date of the mergers and the actual completion dates can be established and verified; ii) both the target and the acquirer should be domestically domiciled in the US, iii) financial firms were not considered, because they are heavily regulated. These restrictions reduced the final sample to 396 potential targets and acquirers that successfully completed mergers and acquisitions and were used in the study. The daily stock price returns (adjusted for dividends and stock splits), trading volume, the market capitalization values are obtained from the Center for Research in Security Prices (CRSP) equal-weighted index database. The excess market return i.e., overall market return less the risk-free rate, SMB, HML and MOM were collected from the Kenneth French website. The risk-free rate is the daily three months annualized US treasury bill rate, but de-annualized for one-day. We calculate the ARs over 11-day event-window, i.e., t–5 to t+5.

3. METHODOLOGY

The Carhart's four-factor model (1997) under the standard OLS specification can be stated as follows:

$$R_{i,t} - R_{f,t-1} = \alpha + \beta_i \left(R_{m,t} - R_{f,t-1} \right) + \\ + \lambda_i SMB_t + \gamma_i HML_t + \delta_i MOM_t + \varepsilon_{i,t}, \quad (1)$$

where α indicates the constant, $R_{i,t}$ indicates the raw stock return for stock i, $R_{f,t-1}$ indicates the risk-free rate for day t, $R_{m,t}$ indicates the overall return on the composite stock index. Thus, $R_{i,t} - R_{f,t}$ indicates the daily excess stock return. Correspondingly, $R_{m,t} - R_{f,t}$ denotes the daily excess market return. In equation (1), SMB_t indicates the difference in portfolio returns between a portfolio comprising of large-sized firms and a portfolio comprising of small-sized firms; HML_t indicates the difference in the portfolio returns comprising of one portfolio of high book-to-market value stocks and another portfolio of low book-to-market value stocks; MOM_t indicates namely the difference between portfolio returns comprising of a portfolio of past winner stocks and another portfolio comprising of past loser stocks, $\varepsilon_{i,t}$ indicates the error term.

The mean equation for the GJR-GARCH-M specification using the Carhart four-factor CAPM is:

$$R_{i,t} - R_{f,t-1} = \alpha + \beta_i \left(R_{m,t} - R_{f,t-1} \right) + \\ + \lambda_i SMB_t + \gamma_i HML_t + \delta_i MOM_t + \\ + \psi_i h_{i,t}^2 + \varepsilon_{i,t}. \quad (2)$$

In equation (2), the coefficient ψ_i is often interpreted as a measure of risk tolerance. The remaining variables have the same meaning as in equation (1). We perform bootstrap simulation on all our CAR estimates. The CARs for stock i using either equation (1) or (2) can be estimated using:

$$\varepsilon_{i,t} = AR_{I,t} = \left(R_{i,t} - R_{f,t-1}\right) - \\ -\left(\alpha + \beta_i\left(R_{m,t} - R_{f,t-1}\right) + \lambda_i SMB_t + \\ +\gamma_i HML_t + \delta_i MOM_t\right). \quad (3)$$

The cumulative ARs (CARs) for stock i over a window of T days starting one day after the announcement or, alternatively, one day before the announcement is computed as:

$$CAR_{i,T} = \sum_{t-1}^{T} AR_{i,T}, \quad (4)$$

where $AR_{i,T}$ is the AR for stock i up to T days. The average CAR over a window T and starting one day after the event or, alternatively, one day before the event and across all N stocks is written as:

$$CAR_t = \frac{1}{N}\sum_{t-1}^{N} CAR_{i,T}. \quad (5)$$

To test the statistical significance of the average CARs, Boehmer et al. (1991), hereafter, BMP, proposed a standardized cross-sectional method, which is robust to the variance induced by the event to investigate whether each average ARs was significantly different from zero. Because the BMP hypothesis testing involves the concept of standardized abnormal returns, SAR_{it} denotes Brown and Warner (1985) standardised abnormal return for stock i on a day t during the event window, and $\sigma\left(SAR_t\right)$ denotes the cross-sectional standard deviation of the standardized abnormal returns on the day t. The BMP t-statistic is written as:

$$t = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\frac{SAR_{it}}{\sigma\left(SAR_t\right)}, \quad (6)$$

where

$$\sigma\left(SAR_t\right) = \sqrt{1/\left(N-1\right)\sum_{i=1}^{N}\left(SAR_{it} - \overline{SAR_t}\right)^2},$$

$$\overline{SAR_t} = 1/N\sum_{i=1}^{N} SAR_{it}.$$

For multi-day intervals, the BMP t-statistic is the ratio of the average cumulative abnormal returns to its estimated standard deviation, that is:

$$t_{BMP} = \sum_{t=1}^{T}\frac{CAR_T}{\sqrt{\sum_{t=1}^{T}\hat{S}^2\left(CAR_t\right)}}, \quad (7)$$

where $\hat{S}\left(CAR_t\right) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(CAR_{i,t} - \overline{CAR_t}\right)^2}$.

See Table A1 in Appendix A for the descriptive statistics for the explanatory variables.

4. BOOTSTRAPPING SIMULATION

This section presents the bootstrapping simulation performs on the raw return measures. The results may be affected by data snooping biases, since we use the same CARs to test for statistical significance (Lo & MacKinlay, 1990). This is often a major problem in event studies. We use a nonparametric bootstrapping approach to test the CARs for each of the estimation methods. Thus, excess stock returns do not support empirical evidence that data snooping biases in our actual excess returns (Lo & MacKinlay, 1990). Moreover, we need to be convinced that the differences in the results based on the estimation methods are consistent for both acquirer and/or target firms.

Panel A of Table 1 presents the bootstrapping simulation performed on the actual CARs for the target firms using OLS and GJR-GARCH-M methods. We find no severe difference between simulated CARs and raw CARs. The test-statistic cannot reject the null hypothesis that the raw return measures are significantly different from the simulated return measures. As such, we do not find that data snooping biases affect our results.

Panel B of Table 1 shows the corresponding results for the acquirer firms. The results indicate that skewness, kurtosis and Jarque-Bera under the GJR-GARCH method are predictable and significant. We do not find any differences between the raw return measures and the simulated return

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Table 1. Bootstrapping simulations of average cumulative measures for target and acquirer firms around merger announcements

Days	1,000 simulation using OLS estimation method					1,000 simulation using GJR-GARCH estimation method				
	Actual	Bootstrap	Skewness	Kurtosis	Jarque-Bera	Actual	Bootstrap	Skewness	Kurtosis	Jarque-Bera
Panel A										
–5	0.0076	0.0079	–0.1956b	0.1007	6.7964b	0.0061	0.0062	–0.0972	0.0337	1.6227
–4	0.0189	0.0190	0.0049	0.2314	2.2352b	0.0153	0.0155	–0.2728a	0.5206a	23.7014a
–3	0.0130	0.0132	0.0077	0.0623	0.1716	0.0105	0.0110	–0.2006a	0.1823	8.0937a
–2	0.0439	0.0436	0.0226	–0.0644	0.2578	0.0332	0.0334	–0.2816a	–0.1136	13.7585a
–1	0.0550	0.0552	–0.1652b	0.1759	5.8369a	0.0363	0.0367	–0.2702a	0.0263	12.1922a
0	0.3997	0.3998	0.1067	–0.0392	1.9599c	0.3996	0.3996	0.2032a	–0.1216	7.4960a
1	0.1097	0.1097	0.4149a	0.7404a	51.5289a	0.1119	0.1120	0.2496a	–0.2513	13.0116a
2	0.1180	0.1182	0.3686a	0.3417b	27.5105a	0.0172	0.0172	0.3741a	0.1630	24.4360a
3	0.1316	0.1318	0.1052	–0.0228	1.8647c	0.1377	0.1376	0.2314a	0.0447	9.0038a
4	0.1340	0.1340	0.1273	0.1561	3.7175a	0.1469	0.1469	0.1948b	0.1881	7.7967a
5	0.1084	0.1085	0.3179a	0.3202b	21.1188a	0.1243	0.1245	0.0140	0.1905	1.5454
Panel B										
–5	0.0203	0.0202	0.1585b	0.0688	4.3855a	0.0402	0.0404	0.5858a	0.1064	57.6680a
–4	0.0251	0.0253	0.1732b	0.0679	5.1941a	0.0674	0.0675	0.7074a	0.2612c	86.2519a
–3	0.0601	0.0602	0.1073	–0.0907	2.2630b	0.1234	0.1234	0.7505a	0.3982b	100.4704s
–2	0.0921	0.0922	0.1713b	–0.0138	4.8966a	0.1695	0.1697	0.7709a	0.4412a	107.1480a
–1	0.1044	0.1045	0.1437c	–0.0204	3.4569a	0.2002	0.2003	0.8347a	0.5117a	127.0219a
0	0.0263	0.0264	0.1285c	0.1193	3.3472a	0.0416	0.0418	0.1763b	0.1236	5.8149a
1	0.0409	0.0410	–0.0874	–0.0006	1.2717	0.0608	0.0609	0.4036a	0.0230	27.1767a
2	0.0399	0.0399	0.0941	0.0074	1.4793	0.0773	0.0774	0.3572a	–0.0624	21.4234a
3	0.0087	0.0088	–0.0295	0.0746	0.3771	0.0682	0.0683	0.6400a	0.5101a	79.1128a
4	–0.0081	–0.0081	–0.0269	–0.0818	0.3989	0.0671	0.0673	0.7715a	0.6118a	114.7907a
5	–0.0177	–0.0179	–0.0725	–0.0510	0.9839	0.0812	0.0813	0.7570a	0.7465a	118.7306a

Note: a, b, c, indicate statistical significance at the 1%, 5% and 10% level, respectively. The simulations are performed on the average AR measures with replacement using 1,000 runs.

measures. As expected, the Jarque-Bera statistic confirms that the raw AR measures are not normally distributed for both estimation methods, but non-normality is more severe under the GJR-GARCH-M method.

5. RESULTS

The analysis of the financial crisis period as of July 2007 to the end of March 2009, many economists describe it as the worst economic disaster since the Great Depression of 1929. However, we argue that the sample is too short for this analysis as there would be too few mergers and acquisitions during the period. Most firms were unwilling or unenthusiastic about mergers and acquisitions during the financial crisis. Empirical studies of Mohamad et al. (2013, p. 10) using UK financial data "find no significant difference in mean abnormal returns in valuation short for either the pre-/post-financial crisis or pre-/post short-selling ban subsample".

5.1. Announcement-period returns

Panel A of Table 2 shows the results for targets under both methods. We test the statistical significance of the CARs using the BMP test statistic. On announcement day, $t = 0$, CARs for the target firms are significant over six-day event window t–1 to t+4 under the OLS method, whilst CARs, under the GJR-GARCH-M method, are significant over eight-day event window t–2 to t+5, respectively. Specifically, CAR on the announcement day $t = 0$ is 3.997% (12.159a = BMP-test) and 3.996% (12.359a = BMP-test), respectively, under both OLS and GJR-GARCH-M method, is highly significant at 1% level. The positive and significant CAR on the announcement day $t = 0$ shows that investors observe the announcement of mergers and acquisitions as essential to them.

Table 2. ARs and CARs measure for target and acquirer firms around mergers announcements using the four-factor CAPM under the OLS estimation method and the GJR-GARCH estimation method

Days	OLS estimation method				GJR-GARCH estimation method				WILCO	
	ARs	CARs	ASAR	BMP-stat.	ARs	CARs	ASAR	BMP-stat.		
Panel A										
–5	0.076	0.076	0.059	1.184	0.061	0.061	0.061	1.781c	> –2.775a	> –3.578a
–4	0.113	0.189	–0.013	1.284	0.092	0.153	–0.005	2.003b	> –2.650a	> –3.634a
–3	–0.059	0.130	–0.116	0.069	–0.048	0.105	–0.115	0.898	< –3.279a	> –3.707a
–2	0.329	0.459	0.137	1.463	0.227	0.332	0.144	2.534a	> –2.685a	> –3.915a
–1	0.091	0.550	0.123	2.537a	0.031	0.363	0.117	3.496a	> –3.101a	> –4.082a
0	3.997	3.997	1.037	12.159a	3.996	3.996	1.039	12.359a	> –4.476a	> –4.476a
1	1.097	1.097	0.228	1.786c	1.119	1.119	0.241	1.802c	< –2.291b	< –2.291b
2	0.083	1.180	0.040	1.820c	0.053	1.172	0.033	2.006b	> –0.270	< –1.855c
3	0.136	1.316	0.078	2.543a	0.205	1.377	0.098	3.002a	< –2.869a	< –2.473a
4	0.024	1.340	–0.051	2.221b	0.092	1.469	–0.027	2.952a	< –2.677a	< –3.042a
5	–0.256	1.084	–0.079	1.476	–0.226	1.243	–0.052	2.432a	< –3.474a	< –3.587a
Panel B										
–5	0.203	0.203	0.079	1.030	0.402	0.402	0.093	1.746c	< –1.355	< –2.808a
–4	0.048	0.251	0.030	1.172	0.272	0.674	0.066	2.438a	< –2.027b	< –3.011a
–3	0.350	0.601	0.097	2.073b	0.560	1.234	0.113	3.399a	< –2.444a	< –3.103a
–2	0.320	0.921	0.151	3.284a	0.461	1.695	0.141	4.427a	< –0.912	< –2.700a
–1	0.123	1.044	–0.012	3.143a	0.307	2.002	0.012	4.468a	< –2.213b	< –2.854a
0	0.263	0.263	0.026	0.161	0.416	0.416	0.031	0.399	< –0.326	< –0.326
1	0.409	0.409	0.068	1.093	0.608	0.608	0.093	1.292	< –0.854	< –0.854
2	–0.010	0.399	–0.012	1.280	0.165	0.773	–0.010	1.452	< –1.238	< –0.815
3	–0.312	0.087	–0.162	–0.022	–0.091	0.682	–0.130	0.462	> –2.122b	< –0.974
4	–0.168	–0.081	–0.067	–0.646	–0.011	0.671	–0.072	–0.226	> –1.133	< –1.346
5	–0.036	–0.177	0.034	–0.171	0.141	0.812	0.048	0.248	< –0.702	< –1.380

Notes: a, b, c indicate statistical significance at the 1%, 5% and 10% levels, respectively. BMP *t*-statistics, ASAR-OLS, BMP-OLS, ASAR-GJR, BMP-GJR and WILCO denote Boehmer, Masumed, and Paulsen *t*-statistics, average standardized abnormal returns under OLS, Boehmer, Masumed, Paulsen test under OLS, average standardized abnormal returns under GJR, Boehmer, Masumed, Paulsen test under GJR and Wilcoxon signed rank test. > denotes OLS larger than GJR-GARCH, < denotes OLS smaller than GJR-GARCH.

These results are in line with those of Soongswang (2011) and Kyei-Mensah (2011) who find positive and significant CARs for target firms on the announcement date. The Wilcoxon signed ranked statistic indicates that typically, the OLS underestimates the magnitude of the CARs relative to the GJR-GARCH-M.

Panel B of Table 2 shows the corresponding results for acquirer firms. The CARs on announcement day $t = 0$ and post-event are positive and insignificant under both specifications, except t–4 to t–5, which is negative under the OLS method. The positive CARs perceived on the pre- and post-event windows are synergies and that US acquirer receives synergies. Interestingly, our results show that there are no short-term negative post-CARs for US acquirers under the GJR-GARCH-M method. These findings are generally consistent with Ben-Amar and Andre (2006) and Dutta and Jog (2009) for Canadian acquirers.

5.2. Cumulative abnormal returns, market liquidity and trading volume

We use the market capitalization value and trading volume of each firm to capture the impact of liquidity and size on the magnitude of CARs for stocks that are associated with mergers and acquisitions. We test for the effects of size and liquidity by dividing the firms into three equal groups (small, mid and large stocks), using, in turn, their market capitalization and trading volume.

5.2.1. Target firms market capitalization

Panel A of Table 3 shows the result of the target firms according to market capitalization value under the two specifications. The CARs on announcement day $t = 0$ for both small- and large-caps are positive and significant at 1% level under OLS and GJR-GARCH-M method. The CARs for

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mid-caps over eleven-day event window, *t*–5 to *t*+5, are positive and significant under both estimation methods. Mid-caps might have appeal to investors after the announcement leading to unparalleled returns. As expected, the persistence in CARs is considerably higher under the GJR-GARCH-M method relative to OLS method. We do not know why mid-caps depict bigger CARs relative to small-caps. Mazouz et al. (2009) and Kyei-Mensah (2011) indicate that due to the dominance of firm ownership in small firms, small-caps ought to have been produced bigger returns relative to mid-caps.

5.2.2. Acquiring firms market capitalization

The corresponding results for the acquirer are shown in Panel B of Table 3. Over the six-day window *t*–5 to *t*+0, the CARs are positive and significant for small-caps under the OLS and GJR-GARCH-M method. On announcement day $t = 0$, the CARs for large-caps are significant under the OLS and GJR-GARCH-M methods, whilst CARs for mid-cap are insignificant under the two estimation methods. Accordingly, small-caps convincingly outperformed mid- and large-caps on the announcement day. As expected, the positive return and significant CARs on the announcement day $t = 0$ for small-caps show that the investors observe the announcement of mergers and acquisitions as essential. We find significant pre-event CARs for small-caps for the period *t*–5 to $t = 0$ under the two estimation methods. This suggests possible information leakages in the financial system, which has policy implications for financial regulators. The CARs in the post-event window were primarily negative under the medium- and large-caps show that hubris hypothesis exists (Roll, 1986). So, following the announcement, the market does not react to any changes in the returns of acquirers' stocks. Grossman and Hart (1980) also suggest that the ARs of bidders will be zero if investors do not

Table 3. Cumulative ARs measures around mergers announcements group by market capitalization value for target and acquirer firms

Days	OLS estimation method							GJR-GARCH estimation method						
	SMALL		MEDIUM		LARGE		K-W	SMALL		MEDIUM		LARGE		K-W
	CARs%	BMP	CARs%	BMP	CARs%	BMP		CARs%	BMP	CARs%	BMP	CARs%	BMP	
Panel A														
–5	–0.161	–0.136	0.930	3.068a	–0.682	–0.593	2.903a	–0.211	0.491	1.437	3.784a	–1.169	–0.887	5.385a
–4	–0.293	–0.468	0.969	3.431a	–0.226	–0.379	3.184a	–0.271	0.329	1.457	4.287a	–0.824	–0.771	4.900a
–3	0.405	0.069	0.432	2.005b	–0.544	–1.594	1.695c	0.523	1.167	0.962	2.834a	–1.252	–2.080b	4.031a
–2	0.571	0.588	0.832	3.436a	–0.105	–1.105	1.777c	0.337	1.548	1.468	4.519a	–0.875	–1.295	4.299a
–1	0.174	0.632	1.135	3.822a	0.270	0.339	2.371a	–0.182	1.593	1.809	4.950a	–0.586	–0.072	3.926a
0	4.831	7.719a	3.794	7.591a	3.422	5.372a	0.432	5.750	7.677a	4.907	7.963a	3.990	5.428a	0.747
1	2.015	1.392	1.656	1.883c	–0.440	–0.568	3.440a	1.958	1.352	1.810	2.057b	–0.408	–0.317	2.984a
2	1.600	1.294	2.282	2.513a	–0.470	–0.697	5.418a	1.556	1.229	2.478	2.813a	–0.650	–0.628	5.167a
3	1.588	1.319	2.589	3.292a	–0.368	–0.199	5.566a	1.740	1.527	2.795	3.713a	–0.490	–0.064	4.554a
4	1.616	1.318	2.083	2.298b	0.110	0.119	1.995b	1.914	1.810c	2.390	2.900a	–0.168	0.265	2.184b
5	1.270	0.684	1.990	2.589a	–0.180	–0.778	2.823a	1.437	1.327	2.465	3.508a	–0.480	–0.705	3.638a
Panel B														
–5	2.606	2.875a	–0.214	0.083	–0.205	–1.112	6.421a	5.662	3.203a	–0.201	0.361	0.413	–0.454	6.528a
–4	2.876	3.018a	-0.646	-0.502	0.102	-0.381	6.792a	6.507	3.763a	-0.625	-0.086	0.807	0.545	8.513a
–3	3.865	4.191a	-0.728	-0.772	0.244	0.251	8.131a	8.085	4.960a	-0.707	-0.230	0.992	1.157	8.989a
–2	4.566	5.243a	-0.696	-0.425	0.474	0.967	10.876a	9.226	5.911a	-0.712	-0.035	1.239	1.792c	12.259a
–1	4.380	4.148a	–0.220	0.353	0.552	1.019	5.522a	9.514	4.888a	–0.199	0.845	1.357	2.001b	7.018a
0	1.786	2.844a	0.037	–0.352	–1.124	–2.182b	4.671a	2.213	2.930a	0.042	–0.174	–1.097	–2.066b	4.546a
1	1.172	1.154	0.110	0.319	–0.086	0.402	0.522	1.656	1.013	0.098	0.399	0.040	0.824	0.344
2	1.261	1.912a	–0.046	–0.029	–0.077	0.321	1.763c	2.173	1.636	–0.039	0.108	0.125	0.770	1.391
3	0.977	0.868	–0.265	0.076	–0.541	–0.890	2.518a	2.469	0.738	–0.244	0.348	–0.269	–0.286	1.444
4	0.920	1.011	–0.400	–0.573	–0.883	–1.435	4.435a	2.990	1.119	–0.488	–0.718	–0.548	–0.792	2.841a
5	0.706	1.035	–0.254	0.111	–0.952	–1.328	3.061a	3.251	1.141	–0.353	–0.080	–0.552	–0.631	1.600

Note: a, b, c, indicate statistical significance at the 1%, 5% and 10% levels, respectively. The statistical significance of CARs is estimated using BMP *t*-statistics. K-W donates Kruskal-Wallis test of the Chi-Square value and test statistics.

Table 4. Cumulative ARs measures around merger announcements group by trading volume for target and acquirer firms

Days	OLS estimation method							GJR-GARCH estimation method						
	SMALL		MEDIUM		LARGE		K-W	SMALL		MEDIUM		LARGE		K-W
	CARs%	BMP	CARs%	BMP	CARs%	BMP		CARs%	BMP	CARs%	BMP	CARs%	BMP	
Panel A														
–5	–0.411	–0.524	0.902	2.391a	–0.457	0.412	2.444a	–0.643	–0.249	1.305	3.096a	–0.699	0.355	3.462a
–4	–0.344	–0.373	0.698	2.036b	0.009	0.787	1.572	–0.499	0.068	1.061	2.746a	–0.337	0.754	1.748
–3	0.158	–0.514	0.341	0.661	–0.324	0.147	0.352	0.091	0.295	0.745	1.299	–0.763	0.026	0.243
–2	0.346	0.042	0.895	2.828a	–0.086	–0.237	1.037	–0.124	0.556	1.427	3.923a	–0.561	–0.111	1.926c
–1	–0.036	–0.068	1.075	3.752a	0.370	0.794	1.567	–0.661	0.324	1.622	4.914a	–0.150	0.735	2.016b
0	5.954	8.216a	5.255	7.086a	3.869	5.672a	0.817	5.836	8.186a	5.399	7.339a	3.840	5.788a	1.251
1	1.600	1.014	1.888	1.854c	–0.109	0.171	0.571	1.550	0.924	1.934	2.017b	0.153	0.506	0.046
2	1.399	1.343	2.130	1.857c	0.242	0.323	0.235	1.390	1.316	2.140	2.006b	0.214	0.521	0.088
3	1.550	1.420	1.923	1.291	0.651	1.926b	0.050	1.702	1.602	1.960	1.630	0.606	2.171b	0.015
4	1.484	1.099	1.808	1.251	0.872	1.885b	0.461	1.770	1.556	1.938	1.770c	0.794	2.114b	0.172
5	1.230	1.091	1.400	0.723	0.721	1.249	0.177	1.480	1.699c	1.680	1.504	0.614	1.460	0.011
Panel B														
–5	1.962	2.221b	0.427	0.742	–0.201	–1.116	2.107b	4.903	2.455a	1.078	1.556	–0.107	–0.901	2.310b
–4	2.171	2.491a	0.567	1.209	–0.405	–1.564	3.221a	5.648	3.116a	1.316	2.277b	–0.275	–1.170	4.272a
–3	2.874	3.195a	0.617	1.542	–0.109	–1.068	2.412a	6.888	3.819a	1.475	2.804a	0.007	–0.736	2.807a
–2	3.282	3.577a	0.825	2.297b	0.238	–0.088	2.710a	7.727	4.040a	1.755	3.695a	0.270	–0.068	3.372a
–1	3.271	2.796a	0.880	2.291b	0.560	0.432	1.114	8.201	3.260a	1.850	3.858a	0.621	0.619	1.671c
0	1.597	2.099b	0.315	0.833	–1.213	–2.622a	5.518a	1.994	2.112b	0.433	1.318	–1.269	–2.739a	6.552a
1	1.603	2.021b	–0.150	–0.030	–0.256	–0.116	4.696a	2.036	1.712c	–0.026	0.351	–0.216	0.174	3.701a
2	1.553	2.498a	–0.024	–0.051	–0.392	–0.243	5.191a	2.351	1.967b	0.233	0.459	–0.324	0.088	3.488a
3	1.439	2.055b	–0.477	–0.987	0.790	–1.013	5.647a	2.808	1.667c	–0.188	–0.429	–0.665	–0.437	3.579a
4	1.207	1.728c	–0.502	–1.133	–1.067	–1.591	5.734a	3.102	1.451	–0.099	–0.462	–1.050	–1.381	4.035a
5	1.351	2.640a	–0.733	–1.395	–1.119	–1.425	5.976a	3.719	2.245b	–0.304	–0.663	–1.068	–1.153	4.378a

Notes: a, b, c, indicate statistical significance at the 1%, 5% and 10% levels, respectively. The statistical significance of CARs is estimated using BMP *t*-statistics. K-W donates Kruskal-Wallis test of the Chi-Square value and test statistics.

expect the gain in the mergers and acquisitions to increase dividend payout to investors. The Kruskal-Wallis test rejects the null hypothesis that the magnitude and direction of the CAR measures are similar across estimation methods.

5.2.3. Target firms trading volume

Panel A of Table 4 illustrates the results for target firms according to trading volume. The results indicate that on announcement day t–0, CARs for small and large trading volume are significant at 1% level under the two estimation methods. Over the five-day event window t–2 to t+2, the CARs are significant at 1% level for the medium trading volume under the OLS and GJR-GARCH-M methods. As before, the persistence of the CARs is much stronger under the GJR-GARCH-M method. On the announcement, small trading volume outperformed both medium and large trading volume. Overall, medium trading volume stocks produced higher returns under the two estimation methods.

5.2.4. Acquiring firms trading volume

Panel B of Table 4 reports the corresponding trading volume for acquirer firms. As expected, the largest gains are among the small firms and have the largest statistically significant gains and the gains decline as the size of the firm increases, such that there are no gains to large acquirers under both the OLS and GJR-GARCH-M methods. The results show that CARs on announcement day $t = 0$ for small trading volume stocks are significant under both estimation methods. Explicitly, the significance of CARs span up to eleven-day window t–5 to t+5 under both methods, except t+4 under the GJR-GARCH-M method. The CARs on announcement day $t = 0$ for the large trading stock are also significant under both methods.

Interestingly, subsequently, small firm acquirers create wealth for their investors, possibly by using their high-value stocks to acquire hard assets of target firms at a discount (Savor & Lu, 2009). The

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persistence and magnitudes of CARs are much stronger under the GJR-GARCH-M method. Using a Kruskal-Wallis test, a nonparametric test rejects the null hypothesis that the magnitude and direction of the CAR measures are similar across estimation methods.

CONCLUSION

We investigate how stock market liquidity impacts the wealth effect of both target and acquiring firms on mergers and acquisitions. On announcement day $t = 0$, US target firms generate a positive return and significant CARs following mergers and acquisitions for an economic benefit under both specifications. Thus, under the GJR-GARCH-M specification, the pre-event CARs are significant and persistent in contrast to the OLS estimate. This suggests possible leakage of information prior to an event announcement and further lends support to the contract theory of information asymmetry and signalling. The CARs on announcement day $t = 0$ for acquiring firms are positive and insignificant. The positive returns perceived during pre- and post-event and on announcement day $t = 0$ suggest that acquiring firms obtain synergies. Our results also show that there are no short-term negative CARs for US acquirers under the GJR-GARCH-M estimation method. For investment purposes, investors will prefer to purchase medium target firms when a takeover is announced. In the same way, rational investors will buy small acquirer firms when a takeover is announced (Kyei-Mensah, 2011). Overall, this research has significant policy implications for managers, investors and financial regulators. One major limitation of this study is the small sample size used; large sample size is encouraged. Further research is needed to report on different variants of the GARCH models exploring asymmetric models.

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APPENDIX A. DESCRIPTIVE STATISTICS

Table A1 shows the descriptive statistics for the explanatory variables used in the four-factor CAPM (see equation (1)). The means of all the variables, i.e., ($R_{m,t}$ – $R_{f,t}$), SMB, HML and MOM are positive. The variance returns of all variables are typically positive. The HML has the smallest standard deviation meaning that it is not as variable relative to ($R_{m,t}$ – $R_{f,t}$) returns, which has the maximum standard deviation. All variables contain significant kurtosis and skewness, which implies that the observations are non-normally distributed. Notice that skewness is typically negative, whereas kurtosis is always positive. The presence of negative skewness is likely to lead to negative asymmetric effects, a feature that can be captured using the GJR-GARCH-M method. Both skewness and kurtosis in the data suggest volatility clustering, which will affect the coefficient estimates under the standard OLS method. The Jarque-Bera shows that the returns for ($R_{m,t}$ – $R_{f,t}$), SMB, HML and MOM are non-normally distributed and are significant. Overall, the data contain statistical properties that can be captured better by the GJR-GARCH-M method compared to the OLS method.

Table A1. Descriptive statistics of explanatory variables

Variables	Mean	Std. dev.	Variance	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
$R_{m,t} - R_{f,t}$	0.012	1.050	1.142	9150	–8.000	–0.126[a]	11.542[a]	19245.650[a]
SMB	0.003	0.375	0.242	5470	–3.420	–0.245[a]	7.225[a]	4655.586[a]
HML	0.012	0.352	0.241	4290	–3.500	–0.175[a]	8.652[a]	10489.280[a]
MOM	0.034	0.463	0.504	6350	–6.350	–1.205[a]	12.251[a]	22655.180[a]

Note: This table presents the descriptive statistics of explanatory variables over the period from January 1, 2004 to December 31, 2014. Std. dev. denotes the standard deviation. a denotes statistical significance at 1% level. The statistical significance is estimated usings student t-statistics.