Abnormal returns around mergers and acquisitions for US firms*

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Abstract

We examine the cumulative abnormal returns (CARs) surrounding merger announcements for NYSE, NASDAQ and AMEX-listed firms. We estimate the Fama-French-Carhart four-factor CAPM under both the standard OLS method and the asymmetric GARCH(1,1)-in-mean, hereafter GJR-GARCH-M. The statistical significance of the CARs is determined using the adjusted Boehmer et al. (1991) t-statistics modified by Kolari and Pynnonen (2010). The GJR-GARCH-M method provides stronger support for the view that shareholders of both acquirers and targets gain around merger announcements. To illustrate, at the announcement date, the CAR of 0.233% is insignificant under the OLS for acquirers, whereas, the CAR of 0.386% is significant under the GJR-GARCH-M method. The gain of 0.386% is sizable supporting the neoclassic theory of M&A. Small and low liquidity acquirers and targets exhibit larger CARs than their medium counterparts. Cash and mixed payments are associated with significant CARs but not stock payments.

Keywords: Mergers and acquisitions (M&As), Abnormal returns, GJR-GARCH-M, Bootstrapping simulations

JEL Classification: G31; C32; C34

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1 Introduction

Empirical studies have advocated different theories to explain the motives for mergers and acquisitions (M&As). If M&As pose a threat to operationally inefficient firms, then under rational conditions, M&As should lead to an increase in shareholders' wealth for both acquirer and target firms, which can be captured via an increase in the abnormal returns (ARs) of the associated firms. Despite this view, empirical studies almost universally indicate the acquirer shareholders do not gain any increase in wealth around merger announcements. The ARs around merger announcements are either zero or negative and significant for acquirer firms (see e.g., Sudarsanam and Mahate, 2003; Gregory and McCorriston, 2005; Ben-Amar and Andre, 2006; Campa and Hernando, 2006; Rosen, 2006; Sudarsanam and Mahate, 2006; Dutta and Jog, 2009; Taoa et al., 2016; Tarabay and Hammoud, 2017; Nguyen et al., 2017). This result holds fairly consistently except when targets are unlisted (see, Faccio et al., 2006; Fuller et al., 2002). In contrast, the ARs of targets are generally positive and significant (see, Jensen and Ruback, 1983; Jarrell et al., 1988; Andrade et al., 2001; Goergen and Renneboog, 2004; Borges and Gairifo, 2013: Panagiotaki, 2015; Rani et al., 2015). Literature has quickly developed in particular to take into account potential endogeneity occurring within a particular event window (Freyaldenhoven, et al., 2019; Thompson and Kim, 2020).

Our study is motivated by several considerations. First, 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

Cahart (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 M&A 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]

Second, prior M&A studies tend to capture ARs using the standard OLS method despite the problems posed by the conditional volatility and asymmetry in the returns, particularly when daily returns are used (see Baillie and Bollerslev, 1989). Time-varying volatility and asymmetry are particularly pronounced in the returns around the announcement period. So the magnitude of the ARs can depend on the volatility of the returns (see, e.g., French et al., 1987). The excess volatility around the announcement period and its impact on ARs is well-known. This is the reason that researchers have provided several tests of statistical significance aimed at dampening the effects that the event-induced variance can have on the ARs around the announcement period (see Brown and Warner, 1985; Boehmer et al., 1991). While some of the statistical tests have had limited success in dealing with the problems posed by event-induced variance in the ARs, not much consideration has been given to the choice of the estimation method that generates the ARs. Indeed, most prior studies estimate the ARs using linear methods, especially the OLS method. The OLS method does not perform well in the presence of heteroscedasticity even if the parameter estimates are still unbiased.[3] GARCH-type

[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] The Draper and Paudyal (2006) use both the Fama-French three-factor and a 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.

[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 autocorrection is not applicable in our case as we estimate the ARs using the regression residuals.

estimation methods tend to lead to greater estimation efficiency over the OLS method (see Corhay and Rad, 1996; Joseph and Mazouz, 2010). For this reason, we estimate the four-factor CAPM using the (asymmetric) GARCH(1,1) in-mean method in line with Glosten et al.'s (1993) specification, hereafter GJR-GARCH-M. An asymmetric GARCH is important because of the tendency for negative news to have more pronounced effects on returns than positive news – the leverage effect. To the best of our knowledge, this is the first study in M&A that estimates the four-factor CAPM using the GJR-GARCH-M estimation method.[4] The novelty in this study is to re-examine whether acquirers lose or gain nothing around merger announcements after permitting for both a proper CAPM approach 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. If targets are the only source of positive gains in M&As, under rational expectation we would expect the gain or loss to acquirers to vary with the form of payment.

Finally, the volatility of the ARs clusters around the event date and this clustering can lead to over-rejection of the null hypothesis of zero ARs. Whilst several statistical tests have been put forward to deal with this problem (see, Brown and Warner, 1980; Boehmer et al., 1991, hereafter, BMP), these tests are not without problems. Recently, Kolari and Pynnonen (2010) modified the BMP *t*-statistic as well as other tests to develop new versions of some of the existing tests. They find that their adjusted-BMP *t*-statistics deal much better with the event-induced volatility and cross-correlation than their other adjusted tests (Kolari and Pynnonen, 2010). For this reason, we test the statistical significance of our cumulative ARs (CARs) using the adjusted-BMP *t*-statistic. In brief, the approach seeks to validate the neoclassic theory of M&As under the assumptions that both our pricing model and estimation method are appropriate.

To summarise our results, we find that under the OLS method, merger announcements do not lead to any wealth creation for shareholders of US acquirers. However, merger announcements do lead to wealth creation for

[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. The Balaban and Constantinou (2006) provide one of the few studies to estimate the ARs using asymmetric GARCH.

acquirers under the GJR-GARCH-M method. Specifically, the average CAR of 0.233% at the event date for acquirers under the OLS method is not significant whereas, the average CAR of 0.386% at the event date is significant under the GJR-GARCH-M method. Indeed, acquirers gain a 5-day significant CAR of 1.907% under the GJR-GARCH-M whereas the 5-day CAR of 1.056% under the OLS is insignificant. Also, target shareholders gain under both estimation methods. The significant CARs for targets span a two-day window under the OLS compared with 4 days under the GJR-GARCH-M. So the GJR-GARCH-M method always outperforms the OLS method. The use of cash and mixed payment methods tends to be associated with significant CARs under both estimation methods but more so under the GJR-GARCH-M method than the OLS method. We also find that smaller capitalization and trading volume acquirers and targets generate larger positive and significant CARs than their medium-sized counterparts. In contrast, the CARs for large capitalization and large trading volume acquirers and targets are largely insignificant. The estimation method substantially affects the magnitude of the CARs and therefore the tendency to reject the null for all characteristics of acquirers and targets. Our preference is to estimate that CARs using the GJR-GARCH-M as opposed to the OLS method.

The remaining sections of this paper are as follows: Section 2 presents the methodology and the data set while the empirical results are presented in section 3. The paper concludes in the final section.

2 Methodology and Data

2.1 Methodology

To capture the ARs, we estimate a four-factor CAPM based on the F-F-C pricing factors. We estimate this four-factor CAPM since there is growing empirical evidence that the basic CAPM neglect size, value, and momentum effects that are important anomalies to be captured in pricing models (see, Loughran and Ritter, 1995; Brav et al., 2000; Jegadeesh, 2000; Mitchell and Stafford, 2000; Moeller, et al., 2005). For the standard OLS method, the four-factor CAPM can be written as:

$$(R_{i,t} - R_{f,t-1}) = \alpha_i + \beta_i (R_{m,t} - R_{f,t-1}) + \emptyset_i SMB_t + \varphi_i HML_t + \eta_i MOM_t + \varepsilon_{i,t} \, , \quad (1)$$

where α_i denotes a constant; $(R_{i,t} - R_{f,t-1})$ denotes the excess return on stock i; $(R_{m,t} - R_{f,t-1})$ denotes the excess overall return on a composite stock index; $R_{f,t-1}$ denotes the risk-free rate; SMB_t denotes the return on a zero-investment portfolio for the size factor, namely the difference in portfolio returns between a portfolio comprising of big/large-sized firms and a portfolio comprising of small-sized firms; HML_t denotes the return on a zero-investment portfolio for the value factor, namely 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 denotes the return on a zero-investment portfolio for the momentum factor, namely the difference between portfolio returns comprising of a portfolio of past winner stocks and another portfolio comprising of past loser stocks; $\varepsilon_{j,t}$ denotes the error term.

The four-factor CAPM under the GJR-GARCH-M method can be stated as follows:

$$(R_{i,t} - R_{f,t-1}) = \alpha_i + \beta_i (R_{m,t} - R_{f,t-1}) + \emptyset_i SMB_t + \varphi_i HML_t + \eta_i MOM_t + \delta_i h^2_{i,t} + \varepsilon_{i,t} \, , \quad (2)$$

where $h^2_{i,t}$ is the conditional variance for the in-mean component for the GJR-GARCH-M. The coefficient δ_i, is often interpreted as a measure of time-varying risk premium or risk tolerance. We use the in-mean version of the GJR-CARCH since following Merton (1973), it is useful to capture the risk associate with the returns. Furthermore, Arvanitis and Demos (2004) show that the use of the in-mean version of the GARCH method has favourable impacts on both skewness and kurtosis in conditional errors. These impacts are important as they provide suitable "corrections" to the patterns in the conditional errors which in turn we use as our ARs (see below). The other parameters of Eq. (2) are interpreted in a similar way to Eq. (1).

To complete the specification of the GJR-GARCH-M method, we state the variance equation as:

$$h^2_{i,t} = Var(\varepsilon_{i,t} | \Omega_{t-1}) = \mu_i + \vartheta_i \varepsilon^2_{i,t-1} + \lambda_i h^2_{i,t-1} + \varpi_i S^2_{i,t-1} \varepsilon^2_{i,t-1} \, , \quad (3)$$

where μ_i is the coefficient for the permanent component of conditional variance; the coefficients ϑ_i and λ_i respectively capture the impacts of past news and lagged conditional volatility; the coefficient ϖ_i captures the asymmetric impact of news, i.e., the leverage effect. Here, $S^2_{i,t-1}$ is a dummy variable that is set to 1 if $\varepsilon^2_{i,t-1}$ is negative, and 0 otherwise. The GJR-GARCH-M method is estimated under the assumption that the conditional errors follow a generalised error distribution. The coefficient estimates of Eq. (3) are not specifically relevant for our purposes, except to the extent that the use of the GJR-GARCH-M leads to better estimates of the conditional errors, $\varepsilon_{j,t}$ which in turn represent our ARs. As such, we ignore the parameter estimates for Eq. (3) when we present our results.

The efficient market hypothesis (EMH) is concerned with the relationship between stock prices and information. According to the EMH, in an efficient market the price of a security fully and fairly reflects all available and relevant information. This means that it is not possible to consistently outperform the market by using any information that the market already knows, except through luck. There is empirical evidence in favour of semi-strong form efficiency. However, the current excess return is predicted by the conditional volatility of previous returns, which violates the efficient market hypothesis. The EMH literature is inconclusive due to the overreaction and returns continuation which is based on momentum strategy. Hong and Stein (1999), Lee and Swaminathan (2000), Jegadeesh and Titman (1993, 2002), design a behavioural model to capture the momentum phenomenon and disprove the efficient market hypothesis. Nevertheless, Fama (1998) put a remarkable comment that under the efficient market hypothesis the expected value of ARs is zero and that the market underreaction and overreaction occurs by chance. This argument is still being debated in the finance community. Another counterargument against the EMH is the excess volatility exhibited in financial stock markets.

Engle and Ng (1993) show that the conditional variance of the GJR-GARCH-M method generates a more reliable asymmetry measure than the EGARCH model. However, since $S^2_{i,t-1}$ is unbounded for negative values, this can lead to unreliable estimates of the ARs, if heteroscedasticity is still present in the conditional residuals (see Nam et al., 2003). Indeed, Nam et al. (2001; 2002) show that the serial correlation following negative return shocks is weaker than the serial correlation following positive return shocks. Both considerations can affect the reliability of our ARs. Systematic risk is the variability of return on stocks or portfolios associated with changes in return on the market as a whole. The systematic risk moves in the opposite direction with overall market volatility – negatively linked associated with large firms or stocks and moves in the direction of the overall market volatility – positively linked associated with small firms or stocks (Hisham and Gazi, 2018). This is consistent with Schwert and Seguin (1990) who find that systematic risk of overall market volatility (negative linked) is associated with large firms or stocks and systematic risk of overall market volatility (positive linked) is associated with small firms or stocks.

To address these issues, we perform bootstrap simulations on all our AR estimates.

Using Eqs. (1) and (2), the AR for stock i is estimated as:

$$AR_{i,t} = \left(R_{i,t} - R_{f,t-1}\right) - \left[\hat{\alpha}_i + \hat{\beta}_i\left(R_{m,t} - R_{f,t-1}\right) + \hat{\emptyset}_i SMB_t + \hat{\varphi}_i HML_t + \hat{\eta}_i MOM_t\right] \quad (4)$$

The CAR for stock i over a window of T days starting one day after the announcement date or alternatively, one day before the announcement date is the summation of $AR_{i,t}$ such that

$$CAR_{i,T} = \sum_{t=1}^{T} AR_{i,t} \, . \quad (5)$$

The average CAR_T of all N stocks over a window T and starting one day after the event or alternatively one day before the event date can be stated as:

$$CAR_T = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,T} \, . \quad (6)$$

The BMP t-statistic is often used to test the significance of the CARs as it accounts for effects of event-induced variance around the announcement period. The BMP t-statistic is given as:

$$t_{BMP} = \frac{1}{N}\sum_{i=1}^{N} \frac{SAR_{i,t}}{\hat{S}(SAR_t)} \, , \quad (7)$$

where $\hat{S}(SAR_t) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(SAR_{i,t} - \overline{SAR_t})^2}$; $\overline{SAR_t} = \frac{1}{N}\sum_{i=1}^{N} SAR_t$. Here, $SAR_{i,t}$ denotes the Brown and Warner (1985) standardized AR for stock i on day t, during the event-window whereas, $\hat{S}(SAR_t)$ denotes the cross-sectional standard deviation of standardized AR on day t. For multi-day intervals, the BMP t-statistic is the ratio of the average CARs to its estimated standard deviation. That is:

$$t_{BMP} = \sum_{t=1}^{T} CAR_T / \sqrt{\sum_{t=1}^{T} \hat{S}^2(CAR_t)}, \tag{8}$$

$$\hat{S}(CAR_t) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(CAR_{i,t} - \overline{CAR_t})^2} \tag{9}$$

Event studies are prone to cross-sectional correlation among the ARs. This means that the independence of the ARs cannot be assured. Harrington and Shrider (2007) show that cross-sectional variation in the effect of event dates always produces event-induced variance. When the cross-correlation is relatively low, event date clustering leads to over-rejection of the null hypothesis of zero AR when in fact the null is true. As such, Kolari and Pynnonen (2010) further modify the BPM t-statistic to account for both the cross-correlation and inflation due to event-induced variance. Their adjusted-BPM t-statistic, hereafter *adj.* BPM is shown to have better power relative to other statistical tests including their adjusted version of the Patell t-statistic.

The *adj.*BMP t-statistic (see Kolari and Pynnonen, 2010) is given by $t_{BMP}\sqrt{\frac{1-\bar{r}}{1+(n-1)\bar{r}}}$,where $\bar{r}$ is the average of the sample cross-correlations of the estimation-period residuals. Assuming that, the square-root rule of the standard deviation of returns over different return periods remains the same for the CARs, $\sqrt{\frac{1-\bar{r}}{1+(n-1)\bar{r}}}$ is the correlation factor for the *adj.* BMP t-statistic.

2.2 Data

To estimate the ARs around the merger announcements, we identify all available M&A stock price returns adjusted for dividends and stock splits for M&A announcements on NYSE, NASDAQ and AMEX-listed firms over the period January 1, 2005, to December 31, 2015, using Thomson One Banker. The data of M&A events are obtained from the M&As Database in Thomson One Banker. Acquiring firms should be public. The data on the following firm's deal characteristics were obtained. The percentage of the acquired stake should be at least 50%, with the percentage of final stake at least 90% of the target. After this initial screening, we obtained 798 M&As data. To be included in the final sample, acquirers and targets have to satisfy the following criteria: i) both the announcement and completion dates could be verifiable for the same firm using financial data, e.g., the form of payment, from Thomson One Banker; ii) the announcement should lead to successfully completion of the merger during the sample period. Foreign domiciled firms are excluded from the sample. The final sample consists of 410 acquirers and targets that successfully completed the M&As. Data on daily stock price returns, trading volume, and market capitalization of both acquirers and targets are collected from the CRSP database. The risk-free is based on the U.S. 3-month Treasury bill rate, available on the U.S. Treasury website, but de-annualized for one day. The daily excess market return, SMB, HML and MOM factors are obtained from the Kenneth French website.[5] We compute the ARs over a 21-day event-window, i.e., $t-10$ to $t+10$, since the short-window studies have been shown to provide most reliable estimates of the gains/losses arising around merger announcements (see Andrde et al., 2001).

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library. We thank Professor Kenneth French for allowing public use of this data. We make a small adjustment to the excess market return by adding back the US Treasury bill rate to obtain the raw market return. This is because we wanted to use a Treasury bill rate that fluctuates daily for all our excess stock return calculations.

3 Empirical Results

3.1 Descriptive statistics

Table 1 depicts the descriptive statistics for the explanatory variables. The mean log-returns are positive for $(R_{m,t} - R_{f,t})$, SMB, HML and MOM, and both HML and MOM are significantly non-zero (p-value < 0.05). The variables show strong variation in the level of kurtosis and skewness, which implies that the observations are non-normally distributed. Negative skewness leads to negative asymmetric effects, a feature that can be captured using the GJR-GARCH-M method. The Q-statistics for the square of the variables also confirms the presence of ARCH effects. For comparison, we estimate the four-factor CAPM using both the standard OLS method and GJR-GARCH-M method.

Table 1. Descriptive statistics of explanatory variables

Variables	N	Mean	Std. dev.	Skewness	Kurtosis	Auto(1)	Auto(2)	Auto(3)	Auto(4)	Auto(5)
$R_{m,t} - R_{f,t}$	5,296	0.022	1.080	–0.198[a]	13.837[a]	0.262	22.524[a]	26.042[a]	30.027[a]	39.681[a]
SMB_t	5,296	0.002	0.567	–0.367[a]	7.862[a]	8.762[a]	8.858[a]	14.091[a]	23.721[a]	25.976[a]
HML_t	5,296	0.016[b]	0.559	0.150[a]	10.723[a]	86.124[a]	88.847[a]	88.936[a]	89.854[a]	96.851[a]
MOM_t	5,296	0.044[a]	0.782	–1.032[a]	14.191[a]	275.430[a]	277.160[a]	282.000[a]	283.110[a]	287.980[a]

This table presents the descriptive statistics of explanatory variables over the period January 1, 2005 to December 31, 2015. *Std. dev.* denotes the standard deviation. Auto (n) denotes the Q-statistic for autocorrelation based on the square of the variables at various lags. [a] and [b] denote statistical significance at the 1% and 5% level, respectively.

3.2 Abnormal returns of acquirer and target firms

If stock markets are informationally efficient then stock prices should adjust quickly to the information contained in merger announcements. Traditionally, researchers expect the price adjustment to take place within the 3-day event-window surrounding the merger announcement, namely day t –1 to t +1 (see, e.g., Andrade et al., 2001). The average ARs, CARs, and SARs for acquirers and targets under both the OLS and GJR-GARCH-M estimation methods are shown in Table 2. Throughout, we test the statistical significance of the (average) CARs using the *adj.* BMP t-statistic.

Table 2. Average abnormal return measures using four-factor CAPM for OLS and GJR-GARCH-M method

	OLS estimation				GJR-GARCH-M estimation				Wilcoxon test		
Days	ARs	CARs	SARs	*adj.* BMP	ARs	CARs	SARs	*adj.* BMP	ARs	CARs	SARs
Panel A: Acquirers											
–10	0.385	0.385	–0.820	–0.11	0.552	0.552	4.617	0.63	4.51[a]	4.08[a]	4.36[a]
–9	0.003	0.388	–3.800	–0.51	0.247	0.799	4.957	0.67	4.23[a]	4.64[a]	3.80[a]
–8	0.031	0.419	–4.055	–0.55	0.271	1.070	2.610	0.35	2.91[a]	3.65[a]	3.65[a]
–7	0.065	0.484	4.877	0.66	0.270	1.341	9.392	1.27	4.23[a]	3.06[a]	4.22[a]
–6	0.041	0.526	–0.247	–0.03	0.215	1.556	3.788	0.51	5.05[a]	4.22[a]	4.91[a]
–5	0.203	0.729	–1.116	–0.15	0.402	1.958	4.300	0.58	3.80[a]	3.06[a]	4.64[a]
–4	0.048	0.778	3.111	0.42	0.272	2.230	9.672	1.31	4.64[a]	2.91[a]	4.08[a]
–3	0.350	1.127	7.814	1.06	0.560	2.790	9.326	1.26	5.05[a]	3.36[a]	4.64[a]
–2	0.321	1.448	9.547	1.29	0.461	3.251	15.628	2.12[b]	4.23[a]	3.36[a]	4.36[a]
–1	0.123	1.570	8.069	1.09	0.307	3.557	13.694	1.85[c]	5.18[a]	3.36[a]	4.08[a]
0	0.233	0.233	5.583	0.76	0.386	0.386	14.479	1.96[b]	6.08[a]	3.50[a]	5.82[a]
1	0.399	0.399	7.139	0.97	0.598	0.598	13.784	1.87[c]	5.82[a]	3.51[a]	5.44[a]
2	–0.020	0.379	9.537	1.29	0.155	0.753	13.198	1.79[c]	5.45[a]	5.45[a]	5.69[a]
3	–0.322	0.057	–7.964	–1.08	–0.101	0.652	–4.806	–0.65	4.91[a]	3.50[a]	4.36[a]
4	–0.178	–0.121	–6.794	–0.92	–0.001	0.651	–3.577	–0.48	5.70[a]	3.65[a]	6.07[a]
5	–0.046	–0.167	3.392	0.46	0.131	0.782	8.435	1.14	5.18[a]	4.08[a]	5.18[a]
6	0.056	–0.111	–3.114	–0.42	0.266	1.048	0.963	0.13	4.64[a]	3.65[a]	3.50[a]
7	0.112	0.002	3.487	0.47	0.319	1.368	8.652	1.17	4.51[a]	4.36[a]	4.91[a]
8	–0.117	–0.115	–4.763	–0.65	0.069	1.437	0.213	0.03	4.92[a]	4.08[a]	5.18[a]
9	0.006	–0.109	2.486	0.34	0.176	1.613	7.495	1.02	4.78[a]	4.78[a]	4.50[a]
10	–0.116	–0.225	–4.046	–0.55	0.116	1.728	2.528	0.34	3.51[a]	4.64[a]	3.21[a]
Panel B: Targets											
–10	–0.285	–0.285	–7.539	–1.02	–0.281	–0.281	–3.715	–0.50	3.07[a]	3.07[a]	2.91[a]
–9	0.053	–0.232	–1.209	–0.16	–0.018	–0.299	3.780	0.51	4.36[a]	4.23[a]	4.08[a]
–8	–0.069	–0.301	–1.266	–0.17	–0.031	–0.330	1.432	0.19	1.82[c]	3.65[a]	1.00
–7	0.322	0.021	6.564	0.89	0.291	–0.039	10.155	1.38	3.66[a]	2.76[a]	2.91[a]
–6	–0.108	–0.087	–1.524	–0.21	–0.047	–0.086	1.380	0.19	2.45[b]	2.45[b]	1.82[c]
–5	0.076	–0.011	2.136	0.29	0.061	–0.025	6.059	0.82	3.36[a]	1.98[b]	4.22[a]
–4	0.113	0.103	–5.573	–0.75	0.092	0.067	–1.153	–0.16	3.36[a]	1.33	3.36[a]
–3	–0.059	0.044	–7.813	–1.06	–0.048	0.019	–5.683	–0.77	2.76[a]	1.65[c]	3.21[a]
–2	0.329	0.373	–0.893	–0.12	0.227	0.246	4.058	0.55	5.05[a]	1.33	5.82[a]
–1	0.091	0.464	8.292	1.12	0.031	0.277	12.415	1.68[c]	2.91[a]	1.82[c]	2.13[a]
0	3.957	3.957	49.940	6.76[a]	3.956	3.956	51.420	6.96[a]	1.33	1.49	1.16
1	1.077	1.077	19.421	2.63[a]	1.099	1.099	22.768	3.08[a]	3.51[a]	1.16	3.65[a]
2	0.063	1.140	9.726	1.32	0.033	1.132	13.678	1.85[c]	3.66[a]	1.49	3.50[a]
3	0.126	1.266	5.791	0.78	0.185	1.317	7.699	1.04	3.51[a]	1.82[c]	2.60[a]
4	0.004	1.270	–7.538	–1.02	0.072	1.389	–5.021	–0.68	2.62[a]	1.65[c]	2.45[b]
5	–0.276	0.994	–9.812	–1.33	–0.246	1.143	–7.627	–1.03	3.21[a]	1.65[c]	2.45[b]
6	0.283	1.277	4.602	0.62	0.249	1.392	7.985	1.08	2.14[b]	1.49	1.16
7	–0.201	1.076	–7.076	–0.96	–0.178	1.213	–5.824	–0.79	3.51[a]	1.16	4.22[a]
8	–0.165	0.911	–8.601	–1.16	–0.165	1.048	–5.975	–0.81	3.36[a]	1.82[c]	2.60[a]
9	0.051	0.962	–1.639	–0.22	0.003	1.051	2.548	0.35	4.09[a]	1.82[c]	3.65[a]
10	–0.157	0.805	–9.126	–1.24	–0.147	0.904	–6.806	–0.92	3.07[a]	1.65[c]	3.36[a]

The AR measures are in percentages. Adj-BPM denotes the adjusted-BPM *t*-statistic. The adjusted BMP *t*-statistics are estimated using the Kolari and Pynnonen (2010) method, which modifies the Boehmer et al. (1991) *t*-statistic for cross-sectional correlation due to event-date clustering. Wilcoxon test is the non-parametric signed rank T^{+} for the difference between the AR measures obtained under the OLS and GJR-GARCH estimations. [a], [b] and [c] denote statistical significance at a 1%, 5% and 10% level, respectively.

Panel A of Table 2 shows that at day *t*, the CAR of 0.233% (*adj.* BMP = 0.76) for acquirers is insignificant under the OLS method, whereas, the

CAR of 0.386% (*adj*. BMP = 1.96) is significant for the GJR-GARCH-M method. The CARs under the OLS method are not significant at any other date. Prior studies often report insignificant CARs or negative and significant CARs for acquirers. So using linear estimation methods, Lang et al. (1989) find insignificant CARs, whereas Hackbarth and Morellec (2008) find a negative and significant CAR of –0.52% over the 3-day event-window t –1 to t +1 for US acquirers. Alexandridis et al. (2010) also find a negative and significant CAR of –1.34% for US acquirers over the t – 2 to t +2 event-window.[6] In contrast, Panagiotaki (2015) also finds insignificant CAR of -1.17% for acquirers over the t -2 to t +2 event-window. The magnitude and statistical significance of abnormal returns around acquisitions (e.g. the negative or insignificant returns of acquirers) have a rational explanation when scholars examine CARs. Morck et al. (1990) hypothesize that bad managers earn significantly negative returns from making acquisitions and the returns are considerably lower than those of good managers. These indicate that firms with superior managers are also superior acquirers. Moeller et al., (2005) argue that the negative returns to acquiring shareholders are due to a trivial number of acquisitions with negative synergy gains by firms with tremendously extreme valuations. While our insignificant CARs under the OLS method are in line with prior work for US acquirers, we also find that the CARs are positive and significant over the entire 5-day window t –2 to t +2 under the GJR-GARCH-M method. Indeed, the Wilcoxon signed ranks test rejects the null hypothesis that the magnitude and direction of AR measures i.e., the ARs, CARs and SARs, are similar across both estimation methods.[7] We attribute the difference in the AR measures to the difference in the estimation methods. So, investors of acquirers expect gains when M&As take place (see Grossman and Hart, 1980). This means that acquirer firms create wealth for their investors, possibly by using their high-value stocks to acquire hard assets of target firms at a discount (see Savor and Lu, 2009). This conclusion, however, applies only to the GJR-GARCH-M results - not the OLS results. So acquirer shareholders can gain an increase in wealth

[6] Using a number of buys and hold benchmark models, Sudarsanam and Mahate (2003) also find that UK acquirer firms generate negative and significant CARs of about 1.40% over the event window t-1 to t +1.

[7] While we show the Wilcoxon signed ranks test, T^{+} for pair-wise comparisons across ±21 days, this test is only meaningful where at least one of the pair of the AR measures for any t is non-zero.

around merger announcements but the estimation method impacts significantly on the results obtained. The use of GARCH methods leads to estimation efficiency gains over the OLS method. The efficiency gains associated with the GJR-GARCH-M method appear to lead to different conclusions regarding the increases or decreases in wealth around merger announcements. Even if the OLS estimates are still the best linear unbiased estimates (BLUE), given that the OLS is a linear model, this does not mean the AR measures under the OLS are entirely reliable. Related empirical work shows that linear estimation methods tend to overestimate (underestimate) the ARs following positive (negative) shocks relative to the GARCH-based estimation method (see Corhay and Rad, 1996; Joseph and Mazouz, 2010). Since we estimate daily returns and there is event-induced clustering around the announcements, we should expect the GJR-GARCH-M method to outperform the OLS under those conditions. So while the CAR for acquirers may be small or even negative, the OLS method seems to bias the results towards zero.

Panel B of Table 2 also shows the CARs for target firms. Under the OLS method, the CAR at day t is 3.957% (*adj*. BMP = 6.76), whereas, the CAR at day t is 3.956% (*adj*. BMP = 6.96) under the GJR-GARCH-M method. For the OLS method, the only other significant CAR is at t +1 in which case the CAR is positive. Sevindik and Gökgöz (2020) find a CAR of 1.80% over the 3-day event window t –1 *to* t +1 and is statistically significant. In contrast, the CARs are positive and significant over the 4-day event-window t –1 to t +2 under the GJR-GARCH-M method. So the GJR-GARCH-M method still outperforms the OLS method by providing stronger evidence of an increase in wealth for target shareholders relative to the OLS. While our CARs for targets are significant under the OLS, our overall evidence is weaker relative to prior US studies. For example, Alexandridis et al. (2010) show that US investors of targets gain a CAR of 5.118% over the 3-day event-window t –1 to t +2 whereas, Panagiotaki (2015): Hackbarth and Morellec (2008) find a relatively larger CAR value of 13.09% and 18.21% respectively, over a similar event-window. So our significant CARs under the OLS are not as spread-out compared to prior US studies. Our 3-day window CAR of 5.125% (5.086%) under the OLS (GJR-GARCH-M) method is closer to the CAR value reported by Alexandridis et al. (2010). However, it seems that the use of the F-F-C pricing factors has reduced the spread of the CARs that are significant under the OLS although not their magnitude. This overall effect reflects the reported impact of the F-F-C pricing factors when used in asset pricing studies (see Carhart, 1997) using linear methods. That is, the pricing factors tend to reduce some of the mispricings in the cross-section of returns. Of course, the comparison of our results with those of prior work must be treated with some caution due to differences in the studies. As before, the Wilcoxon signed ranks test rejects the null hypothesis that the magnitude and direction of the AR measures are similar across estimation methods. So the AR measures are larger under the GJR-GARCH-M method, leading to higher rejection rates. Since the volatility of returns will be greater around the event date (see Brown and Warner, 1985), linear estimation methods, such as the OLS method, are likely to capture the ARs less well.[8] As mentioned earlier, the literature has indicated that pre-event trends are endogenously established, and economic cognitive defends the endogeneity, but statistically they were not able to confirm the endogeneity of pre-event trend variable from their data (Thompson and Kim, 2020). If pre-trends are unnoticed, it could mean that either that there are no pre-trends or that pre-trends are existing but unobserved due to limited statistical power ((Freyaldenhoven, et al., 2019).

3.3 Bootstrap simulation

The above results may be affected by data-snooping biases since we use the same ARs to test for statistical significance (see e.g., Lo and MacKinlay, 1990). This is often a major drawback in event studies. So sampling over an extremely large data set may well reverse our results (see Malliaropulos, 1996). The importance of data-snooping biases should not be underestimated since we find results for acquirers that may be considered contrary to the norm. That is, we find positive and significant CARs for acquirers using the GJR-GARCH-M method when more often than not prior studies tend to report insignificant CARs or negative and significant CARs (see, e.g., Hackbarth and Morellec, 2008). While we attribute the positive and significant CARs under the GJR-GARCH-M method to gains in estimation efficiency, these gains are quite substantial relative to the OLS

[8] The increase in the variance of the returns around the event dates is primarily the reason that researchers have developed several tests to correct for event-induced variance in the cross-section of ARs (see, Boehmer et al., 1991; Savickas, 2003; Kolari and Pynnönen, 2010). The use of our GJR-GARCH-M also provides adjustments to the ARs at an earlier stage in the estimation.

method. Furthermore, we need to be certain that the differences in the results based on the estimation methods are reliable for both acquirer and or target firms.

Table 3. Bootstrap simulations of OLS and GJR-GARCH-M abnormal return measures

	OLS estimation						GJR-GARCH-M estimation					
	ARs		CARs		SARs		ARs		CARs		SARs	
Days	Actual	Boot.	Actual	Boot.	Actual	Boot.	Actual	Boot.	Actual	Boot.	Actual	Boot.
Panel A: Acquirers												
–10	0.385	0.388	0.385	0.388	–0.820	–0.726	0.552	0.560	0.552	0.560	4.617	4.373
–9	0.003	0.003	0.388	0.391	–3.800	–4.035	0.247	0.244	0.799	0.804	4.957	4.621
–8	0.031	0.041	0.419	0.432	–4.055	–3.943	0.271	0.275	1.070	1.079	2.610	2.361
–7	0.065	0.056	0.484	0.488	4.877	4.795	0.270	0.277	1.341	1.356	9.392	9.438
–6	0.041	0.048	0.526	0.536	–0.247	–0.402	0.215	0.212	1.556	1.568	3.788	4.373
–5	0.203	0.199	0.729	0.735	–1.116	1.129	0.402	0.417	1.958	1.985	4.300	4.338
–4	0.048	0.050	0.778	0.785	3.111	2.860	0.272	0.278	2.230	2.263	9.672	9.618
–3	0.350	0.339	1.127	1.124	7.814	7.846	0.560	0.543	2.790	2.806	9.326	9.385
–2	0.321	0.326	1.448	1.450	9.547	9.546	0.461	0.455	3.251	3.261	15.628	15.364
–1	0.123	0.123	1.570	1.573	8.069	8.170	0.307	0.300	3.557	3.561	13.694	14.184
0	0.233	0.233	0.233	0.233	5.583	5.645	0.386	0.375	0.386	0.375	14.479	14.224
1	0.399	0.388	0.399	0.399	7.139	7.530	0.598	0.615	0.598	0.598	13.784	13.752
2	–0.020	–0.018	0.379	0.381	9.537	9.668	0.155	0.148	0.753	0.746	13.198	12.811
3	–0.322	–0.330	0.057	0.051	–7.964	–7.946	–0.101	–0.105	0.652	0.641	–4.806	–4.878
4	–0.178	–0.183	–0.121	–0.132	–6.794	–6.408	–0.001	0.001	0.651	0.642	–3.577	–3.585
5	–0.046	–0.046	–0.167	–0.178	3.392	3.687	0.131	0.137	0.782	0.779	8.435	8.355
6	0.056	0.044	–0.111	–0.134	–3.114	–2.840	0.266	0.262	1.048	1.041	0.963	1.036
7	0.112	0.110	0.002	–0.024	3.487	3.502	0.319	0.314	1.368	1.355	8.652	8.355
8	–0.117	–0.114	–0.115	–0.138	–4.763	–4.834	0.069	0.048	1.437	1.403	0.213	–0.176
9	0.006	0.015	–0.109	–0.123	2.486	2.644	0.176	0.177	1.613	1.580	7.495	7.824
10	–0.116	–0.117	–0.225	–0.240	–4.046	–3.963	0.116	0.102	1.728	1.682	2.528	2.446
Panel B: Targets												
–10	–0.285	–0.281	–0.285	–0.281	–7.539	–7.628	–0.281	–0.286	–0.281	–0.286	–3.715	–3.981
–9	0.053	0.066	–0.232	–0.215	–1.209	–1.284	–0.018	–0.020	–0.299	–0.306	3.780	3.653
–8	–0.069	–0.063	–0.301	–0.278	–1.266	–1.372	–0.031	–0.035	–0.330	–0.341	1.432	1.588
–7	0.322	0.324	0.021	0.046	6.564	6.892	0.291	0.287	–0.039	–0.054	10.155	10.029
–6	–0.108	–0.109	–0.087	–0.063	–1.524	–1.278	–0.047	–0.045	–0.086	–0.099	1.380	1.439
–5	0.076	0.080	–0.011	0.017	2.136	1.730	0.061	0.057	–0.025	–0.042	6.059	5.743
–4	0.113	0.109	0.103	0.126	–5.573	–5.400	0.092	0.095	0.067	0.053	–1.153	–1.385
–3	–0.059	–0.059	0.044	0.067	–7.813	–7.697	–0.048	–0.046	0.019	0.007	–5.683	–5.843
–2	0.329	0.338	0.373	0.405	–0.893	–0.902	0.227	0.222	0.246	0.229	4.058	4.138
–1	0.091	0.075	0.464	0.48	8.292	8.353	0.031	0.030	0.277	0.259	12.415	12.380
0	3.957	3.958	3.957	3.958	49.940	50.071	3.956	3.972	3.956	3.972	51.420	51.773
1	1.077	1.081	1.077	1.077	19.421	18.478	1.099	1.086	1.099	1.099	22.768	22.453
2	0.063	0.061	1.140	1.138	9.726	9.239	0.033	0.045	1.132	1.144	13.678	13.582
3	0.126	0.123	1.266	1.261	5.791	5.883	0.185	0.184	1.317	1.328	7.699	7.944
4	0.005	0.012	1.270	1.273	–7.538	–7.608	0.072	0.077	1.389	1.405	–5.021	–5.041
5	–0.276	–0.275	0.994	0.998	–9.812	–10.011	–0.246	–0.253	1.143	1.152	–7.627	–7.482
6	0.283	0.279	1.277	1.277	4.602	4.522	0.249	0.243	1.392	1.395	7.985	8.436
7	–0.201	–0.205	1.076	1.072	–7.076	–7.207	–0.178	–0.176	1.213	1.219	–5.824	–5.819
8	–0.165	–0.170	0.911	0.902	–8.601	–8.551	–0.165	–0.171	1.048	1.048	–5.975	–6.319
9	0.051	0.046	0.962	0.948	–1.639	–1.717	0.003	0.001	1.051	1.049	2.548	2.682
10	–0.157	–0.164	0.805	0.784	–9.126	–9.312	–0.147	–0.151	0.904	0.898	–6.806	–6.787

The AR measures are in percentages. *Boot.* denotes bootstrap simulations. The simulations are performed on the average AR measures with replacement using 1000 runs.

To test for the potential impacts of data-snooping biases, we run a nonparametric bootstrap simulation with a replacement on the ARs, CARs and SARs of each *t*-day and for each estimation method. Prior studies do not provide clear guidance on the appropriate number of runs for such a simulation. Sullivan et al. (1999) and Jegadeesh and Titman (2002) use 500 draws, for example, whereas Barber and Lyon (1997), Kothari and Warner (1997) and Ahern (2009) use 1000 runs. We run the bootstrap simulations using 500 and 1000 runs with replacement. To save space, we report the results for the 1000 runs. The results for 500 runs are quantitatively similar and are available on request. Table 3 shows the simulation results for ARs, CARs and SARs and the corresponding raw AR measures. As expected, the Jarque-Bera statistic confirms that the raw AR measures are not normally distributed (not shown) for both estimation methods but non-normality is more severe under the OLS method. This result is expected. The bootstrap AR measures are generally normally distributed. The Wilcoxon signed ranks test 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.

3.4 Abnormal returns and payment method

Myers and Majluf (1984) suggest that acquirers will exchange their stocks with target firms if acquirers believe that their own shares are over-valued. In this case, high-value acquirers will use cash offers or a large proportion of the cash payment to signal the higher value of their stocks to the market (see, e.g., Fishman, 1989; Eckbo et al., 1990). Adverse selection on the part of acquirers can cause them to exchange stocks as this allows targets to share in the risk of over-payment if the cash payment is used (see Hansen, 1987; Eckbo and Thorburn, 2000). This argument suggests that acquirers will offer stocks to shareholders of target firms when there is high uncertainty regarding the market value of target firms. In contrast, acquirers will make cash offers when there is high uncertainty regarding their own market value. Thus we predict that the CARs of acquirers will be positive and significant when cash offers are made and negative and significant when stock offers are made. Taking the prevailing view that targets gain more from M&As and acquirers' shareholders gain nothing or lose, we also examine whether the higher gains for targets depend on the form of payment.

3.4.1 Acquirers and payment methods

Table 4a shows the AR measures according to the method of payment. The results are largely in line with our prediction. For both estimation methods, the CARs for acquirers are significant when cash and mixed (cash and stocks) offers are made but are uniformly insignificant when stock offers are made. Chang (1998) also hypothesized negative average price reaction for stock bidders acquiring publicly traded targets. However, the significant AR measures are spread out over a much larger event-window under the GJR-GARCH-M method. Specifically, under the OLS method, the CARs for cash offers are positive and significant over the 3-day event-window $t-1$ to $t+1$ whereas, under the GJR-GARCH-M method the CARs for cash offers are positive and significant over the 5-day event-window $t-2$ to $t+2$. Consistent with the Wilcoxon signed-rank test, the returns are positive and significant under both methods. Heron and Lie (2002), Alexandridis et al. (2010) and Karampatsasa et al. (2014) also find that US acquirers that make cash offers exhibit significant CARs under the OLS method. Mateev and Andonov (2015) also find CARs for the acquirer of domestic acquisitions are significantly higher when a cash payment is made. Chang (1998) further argued that "the positive share price reaction is consistent with the monitoring hypothesis that the creation of an outside block-holder results in an increase in firm value through more efficient monitoring of managers or an increase in the probability of takeovers"(p. 778).

Table 4a. Average abnormal return measures for acquirers using the four-factor CAPM

	OLS estimation				GJR-GARCH estimation				Wilcoxon test		
Days	ARs	CARs	SCARs	*adj.* BMP	ARs	CARs	SCARs	*adj.* BMP	ARs	CARs	SCARs
Panel A: Cash payment											
–10	0.278	0.278	3.817	0.43	0.466	0.466	4.019	0.53	7.18[a]	7.18[a]	6.59[a]
–9	–0.037	0.241	–0.421	–0.06	0.262	0.728	–0.611	–0.08	4.65[a]	6.17[a]	4.65[a]
–8	–0.066	0.175	–6.888	–0.78	0.221	0.949	–8.842	–1.06	4.88[a]	4.65[a]	5.31[a]
–7	–0.015	0.16	–3.796	–0.57	0.245	1.194	–4.859	–0.55	4.88[a]	4.41[a]	5.10[a]
–6	–0.094	0.066	–5.632	–0.64	0.137	1.331	–6.193	–0.88	6.39[a]	5.96[a]	5.75[a]
–5	0.233	0.299	3.409	0.55	0.469	1.800	7.331	0.83	6.97[a]	5.33[a]	5.96[a]
–4	–0.070	0.229	1.668	0.19	0.172	1.972	7.236	0.82	6.17[a]	5.10[a]	5.31[a]
–3	0.592	0.821	8.690	0.99	0.827	2.799	13.496	1.53	6.17[a]	5.54[a]	6.78[a]
–2	0.218	1.039	7.623	0.83	0.440	3.239	16.360	1.89[c]	6.39[a]	4.88[a]	5.75[a]
–1	0.009	1.048	14.156	1.66[c]	0.232	3.471	14.274	1.98[b]	5.55[a]	5.10[a]	6.59[a]
0	0.051	0.051	13.632	1.70[c]	0.274	0.274	17.306	2.09[b]	7.37[a]	5.75[a]	6.97[a]

1	0.299	0.299	13.561	1.68^{c}	0.569	0.569	16.531	1.91^{c}	6.59^{a}	5.54^{a}	6.37^{a}
2	0.033	0.332	11.264	1.28	0.255	0.824	12.464	1.69^{c}	5.98^{a}	5.75^{a}	5.75^{a}
3	–0.315	0.017	5.036	0.57	–0.060	0.764	5.258	0.60	6.17^{a}	5.54^{a}	6.17^{a}
4	–0.254	–0.237	–3.713	–0.42	–0.020	0.744	–4.292	–0.57	7.55^{a}	5.33^{a}	7.91^{a}
5	0.111	–0.126	6.453	0.73	0.353	1.097	6.457	0.73	6.39^{a}	5.54^{a}	5.96^{a}
6	–0.176	–0.302	–1.958	–0.22	0.104	1.201	–2.827	–0.39	5.54^{a}	4.88^{a}	4.65^{a}
7	0.039	–0.263	–2.126	–0.32	0.267	1.468	–3.445	–0.51	5.54^{a}	5.75^{a}	5.96^{a}
8	–0.294	–0.557	–9.661	–1.10	–0.084	1.384	–10.800	–1.21	6.78^{a}	5.96^{a}	7.35^{a}
9	–0.105	–0.662	–10.044	–1.14	0.118	1.502	–8.457	–0.96	5.55^{a}	6.59^{a}	5.54^{a}
10	–0.089	–0.751	–10.824	–1.23	0.202	1.704	–6.854	–0.78	4.19^{a}	6.59^{a}	4.41^{a}
Panel B: Stock payment											
–10	0.452	0.452	6.808	0.83	0.506	0.506	8.414	0.94	1.03	1.03	1.97^{b}
–9	–0.077	0.375	–2.147	–0.24	0.021	0.527	1.274	0.15	0.53	0.53	0.01
–8	0.107	0.482	–4.361	–0.49	0.195	0.722	1.521	0.19	0.53	0.53	1.03
–7	0.749	1.231	7.445	0.82	0.879	1.601	9.981	1.21	1.03	1.09	1.03
–6	0.306	1.537	7.158	0.85	0.403	2.004	12.866	1.43	1.51	0.01	1.51
–5	0.096	1.633	7.628	0.92	0.224	2.228	13.032	1.44	0.53	1.09	2.27^{b}
–4	0.077	1.71	7.090	0.84	0.249	2.477	9.499	1.09	1.51	1.09	1.51
–3	–0.294	1.416	8.050	0.98	–0.191	2.286	9.155	1.02	0.53	1.67^{c}	0.53
–2	0.89	2.306	7.185	0.87	0.952	3.238	13.538	1.52	0.03	1.09	0.01
–1	0.083	2.389	7.532	0.91	0.198	3.436	13.375	1.51	0.54	1.09	0.01
0	0.743	0.743	–0.919	–0.19	0.784	0.784	–3.219	–0.40	1.03	1.67^{c}	1.97
1	0.149	0.149	–0.327	–0.04	0.221	0.221	–0.450	–0.05	1.52	0.53	1.51
2	–0.072	0.077	–5.356	–0.65	0.072	0.293	–8.776	–0.98	1.03	0.01	0.53
3	–0.239	–0.162	–8.558	–0.96	–0.198	0.095	–9.251	–1.13	2.82^{a}	0.01	1.97^{b}
4	–0.488	–0.65	–10.301	–1.13	–0.381	–0.286	–10.777	–1.31	1.03	0.53	1.51
5	–0.438	–1.088	–8.609	–1.08	–0.411	–0.697	–14.341	–1.60	1.51	1.03	1.51
6	0.445	–0.643	–7.010	–0.82	0.579	–0.118	–13.045	–1.39	0.03	0.53	1.09
7	0.274	–0.369	–8.909	–1.08	0.427	0.309	–10.838	–1.13	1.91^{b}	0.53	2.41^{b}
8	–0.381	–0.75	–9.045	–1.10	–0.268	0.041	–11.923	–1.30	1.09	0.01	1.67^{c}
9	0.149	–0.601	–0.881	–0.11	0.203	0.244	–13.517	–1.50	1.51	0.53	1.03
10	–0.152	–0.753	–1.061	–0.13	–0.044	0.200	–8.090	–0.99	1.09	1.03	1.09
Panel C: Mixed stock and cash payment											
–10	0.714	0.714	4.835	0.56	0.939	0.939	8.252	0.96	1.34	1.34	2.31^{b}
–9	0.277	0.991	7.448	1.15	0.483	1.422	8.994	1.41	2.76^{a}	1.83^{c}	2.31^{b}
–8	0.113	1.104	8.246	0.96	0.352	1.774	9.797	1.13	0.28	1.34	0.28
–7	0.041	1.145	7.090	1.11	0.158	1.932	8.462	1.30	1.34	0.82	1.34
–6	0.154	1.299	8.627	1.01	0.282	2.214	11.748	1.36	1.83^{c}	1.83^{c}	2.76^{a}
–5	–0.152	1.147	0.483	0.08	0.062	2.276	6.055	1.00	2.76^{a}	0.82	2.76^{a}
–4	0.952	2.099	9.610	1.18	1.121	3.397	11.406	1.31	1.83^{c}	0.28	1.83^{c}
–3	0.035	2.134	12.822	1.47	0.253	3.65	13.798	1.61	0.28	1.34	0.28
–2	0.278	2.412	10.510	1.27	0.331	3.981	15.433	1.74^{c}	2.31^{b}	1.83^{c}	2.76^{a}
–1	0.689	3.101	14.125	1.65^{c}	0.788	4.769	15.148	1.79^{c}	1.34	0.82	1.83^{c}
0	0.316	0.316	15.265	1.75^{c}	0.412	0.412	16.025	1.92^{c}	3.17^{a}	0.82	1.83^{c}
1	0.663	0.663	11.277	1.62	0.716	0.716	12.876	1.68^{c}	3.94^{a}	0.82	3.17^{a}
2	–0.166	0.497	3.779	0.44	–0.130	0.586	5.045	0.59	1.83^{c}	1.83^{c}	2.31^{b}
3	–0.380	0.117	–3.779	–0.44	–0.101	0.485	0.033	0.01	0.29	0.28	0.29
4	0.247	0.364	0.052	0.01	0.493	0.978	4.643	0.54	0.82	0.28	0.82
5	–0.417	–0.053	–8.529	–0.99	–0.313	0.665	–0.156	–0.02	2.31^{b}	0.82	2.31^{b}
6	0.418	0.365	0.613	0.08	0.554	1.219	4.717	0.54	2.76^{a}	0.82	1.83^{c}
7	0.076	0.441	0.143	0.02	0.261	1.48	3.674	0.57	1.34	1.83^{c}	1.34
8	0.589	1.03	7.558	0.89	0.772	2.252	12.065	1.39	2.76^{a}	1.34	2.76^{a}
9	0.097	1.127	7.842	0.94	0.204	2.456	10.913	1.28	2.31^{b}	1.34	1.83^{c}
10	–0.353	0.774	5.031	0.59	–0.275	2.181	11.659	1.56	2.76^{a}	0.82	1.83^{c}

The AR measures are in percentages. Adj-BPM denotes the adjusted-BPM *t*-statistic. Wilcoxon test is the non-parametric signed rank T^{+} for the difference between the AR measures obtained under the OLS and GJR-GARCH estimations. ^{a}, ^{b} and ^{c} denote statistical significance at a 1%, 5% and 10% level, respectively.

Table 4b. Average abnormal return measures for targets using the

four-factor CAPM

	OLS estimation				GJR-GARCH estimation				Wilcoxon test		
Days	ARs	CARs	SCARs	*adj.* BMP	ARs	CARs	SCARs	*adj.* BMP	ARs	CARs	SCARs
Panel A: Cash payment											
–10	–0.385	–0.385	–1.765	–0.20	–0.372	–0.372	–0.483	–0.05	3.95[a]	3.95[a]	3.95[a]
–9	0.26	–0.125	1.810	0.27	0.181	–0.191	2.978	0.34	5.10[a]	5.33[a]	5.10[a]
–8	0.112	–0.013	2.957	0.34	0.149	–0.042	3.995	0.45	2.46[b]	3.95[a]	1.93[c]
–7	0.155	0.142	4.557	0.69	0.100	0.058	7.437	0.84	4.88[a]	3.47[a]	4.41[a]
–6	–0.206	–0.064	3.209	0.36	–0.111	–0.053	7.274	0.83	2.97[a]	2.97[a]	2.20[b]
–5	0.141	0.077	7.697	1.25	0.096	0.043	14.387	1.63	3.95[a]	2.72[a]	4.88[a]
–4	0.095	0.172	11.233	1.28	0.100	0.143	15.376	1.75[c]	2.21[b]	1.67[c]	1.67[c]
–3	–0.105	0.067	2.710	0.31	–0.090	0.053	17.760	1.88[c]	1.95[c]	1.67[c]	2.20[b]
–2	0.577	0.644	16.362	1.86[c]	0.515	0.568	23.262	2.64[a]	3.47[a]	1.93[c]	3.22[a]
–1	0.158	0.802	20.220	2.30[b]	0.161	0.729	32.290	3.67[a]	2.97[a]	1.93[c]	2.72[a]
0	2.804	2.804	64.595	7.34[a]	2.813	2.813	66.514	7.55[a]	0.60	1.40	0.58
1	0.851	0.851	15.472	1.76[c]	0.873	0.873	16.805	1.88[c]	4.19[a]	1.40	4.65[a]
2	0.007	0.858	14.625	1.66[c]	0.009	0.882	18.610	2.05[b]	5.54[a]	1.14	5.96[a]
3	0.201	1.059	20.859	2.37[b]	0.263	1.145	21.296	2.42[b]	5.54[a]	1.93[b]	4.41[a]
4	–0.237	0.822	14.626	1.66[c]	–0.162	0.983	17.313	1.97[b]	3.74[a]	1.93[b]	3.46[a]
5	–0.236	0.586	11.570	1.31	–0.233	0.750	15.797	1.79[c]	4.88[a]	1.67[c]	3.95[a]
6	0.397	0.983	9.388	1.10	0.356	1.106	12.695	1.39	2.46[b]	1.67[c]	1.40
7	–0.111	0.872	8.739	1.13	–0.065	1.041	10.066	1.52	3.71[a]	1.14	4.41[a]
8	–0.155	0.717	6.931	0.92	–0.139	0.902	9.799	1.11	4.65[a]	1.67[c]	3.71[a]
9	0.098	0.815	9.758	1.24	0.033	0.935	12.376	1.41	5.33[a]	2.46[b]	4.65[a]
10	–0.226	0.589	7.098	0.81	–0.202	0.733	8.958	0.93	3.72[a]	1.93[c]	3.95[a]
Panel B: Stock payment											
–10	0.397	0.397	3.524	0.45	0.226	0.226	6.070	0.77	2.41[a]	2.41[b]	2.41[b]
–9	–0.665	–0.268	2.933	0.38	–0.847	–0.621	–1.717	–0.21	3.60[a]	2.82[a]	2.82[a]
–8	–0.446	–0.714	–6.960	–0.87	–0.560	–1.181	–9.787	–1.23	1.51	3.23[a]	1.03
–7	0.663	–0.051	6.080	0.77	0.579	–0.602	9.753	1.23	2.41[b]	2.41[b]	1.97[c]
–6	–0.001	–0.052	4.923	0.62	–0.039	–0.641	8.370	1.05	1.03	2.41[a]	0.53
–5	–0.391	–0.443	1.199	0.15	–0.444	–1.085	–3.666	–0.47	2.41[c]	2.42[b]	3.23[a]
–4	0.107	–0.336	–1.882	–0.24	–0.040	–1.125	–4.437	–0.56	3.60[a]	1.97[b]	4.31[a]
–3	0.292	–0.044	–7.033	–0.89	0.219	–0.906	–8.443	–1.07	1.97[b]	2.41[b]	2.82[a]
–2	–0.111	–0.155	–0.236	–0.03	–0.693	–1.599	–4.199	–0.53	2.82[a]	1.51	2.82[a]
–1	–0.390	–0.545	–3.393	–0.42	–0.744	–2.343	–7.676	–0.96	1.97[b]	1.97[b]	1.03
0	5.347	5.347	40.639	4.82[a]	5.217	5.217	41.215	4.97[a]	1.51	2.41[b]	1.97[b]
1	2.737	2.737	1.854	0.24	2.655	2.655	6.113	0.77	1.99[b]	1.51	1.51
2	–0.036	2.701	3.496	0.44	–0.245	2.410	6.674	0.84	3.23[a]	2.41[b]	3.96[a]
3	0.077	2.778	8.866	1.11	0.075	2.485	13.651	1.63	0.01	2.41[b]	0.01
4	0.333	3.111	8.983	1.25	0.385	2.870	11.588	1.42	0.53	1.97[b]	1.03
5	–0.481	2.630	6.234	0.78	–0.531	2.339	12.82	1.62	0.01	1.97[b]	0.53
6	0.528	3.158	7.746	0.98	0.453	2.792	11.069	1.39	1.51	1.97[b]	0.53
7	–0.412	2.746	8.330	1.05	–0.536	2.256	12.283	1.55	2.82[a]	1.51	2.82[a]
8	–0.573	2.173	–2.045	–0.26	–0.639	1.617	4.606	0.59	0.01	2.41[b]	0.01
9	0.241	2.414	5.961	0.75	0.174	1.791	11.356	1.43	0.03	1.51	0.01
10	0.315	2.729	9.802	1.25	0.171	1.962	12.275	1.59	2.82[a]	1.51	2.82[a]
Panel C: Mixed stock and cash payment											
–10	–0.642	–0.642	–9.303	–1.10	–0.480	–0.480	–12.881	–1.50	0.82	0.82	2.76[a]
–9	0.073	–0.569	–4.554	–0.71	0.169	–0.311	–7.992	–1.25	4.61[a]	4.28[a]	0.82
–8	–0.263	–0.832	–3.132	–0.36	–0.065	–0.376	–12.041	–1.41	2.76[a]	2.76[a]	2.76[a]
–7	0.454	–0.378	3.283	0.51	0.557	0.181	–5.795	–0.90	4.90[a]	3.56[a]	1.34
–6	0.221	–0.157	–2.550	–0.30	0.28	0.461	8.939	1.05	3.56[a]	3.56[a]	1.34
–5	0.171	0.014	2.077	0.35	0.33	0.791	12.234	1.40	3.17[a]	2.31[b]	0.29
–4	0.398	0.412	13.325	1.56	0.385	1.176	13.353	1.59	3.94[a]	3.17[a]	0.82
–3	–0.403	0.009	2.614	0.30	–0.331	0.845	14.723	1.73[c]	0.82	3.94[a]	0.89
–2	–0.244	–0.235	–2.397	–0.29	0.004	0.849	14.148	1.65[c]	1.34	4.28[a]	0.85
–1	0.453	0.218	4.536	0.53	0.477	1.326	17.944	2.10[b]	2.33[b]	4.28[a]	0.89
0	7.000	7.000	52.918	6.20[a]	7.113	7.113	55.031	6.29[a]	0.82	4.61[a]	0.85

1	−0.062	−0.062	−0.160	−0.02	0.123	0.123	15.278	1.86[c]	0.32	4.56[a]	2.31[b]
2	0.404	0.342	8.268	0.96	0.486	0.609	15.015	1.76[c]	3.59[a]	4.63[a]	0.82
3	−0.119	0.223	7.024	0.83	0.001	0.610	16.370	1.92[c]	1.34	4.85[a]	0.89
4	0.370	0.593	1.648	0.20	0.435	1.045	11.148	1.31	2.33[b]	4.56[a]	2.31[a]
5	−0.139	0.454	−0.568	−0.06	0.085	1.130	11.618	1.37	0.86	4.94[a]	3.56[a]
6	−0.387	0.067	−0.287	−0.03	−0.348	0.782	−11.970	−1.40	0.28	4.45[a]	0.29
7	−0.401	−0.334	−8.145	−1.28	−0.332	0.450	−8.627	−1.29	0.89	4.23[a]	2.76[a]
8	0.186	−0.148	−7.988	−0.93	0.204	0.654	−10.212	−1.19	0.82	4.28[a]	1.83[c]
9	−0.094	−0.242	−11.487	−1.35	−0.087	0.567	−11.919	−1.34	1.36	4.08[a]	1.83[c]
10	−0.409	−0.651	−12.978	−1.53	−0.257	0.310	−13.232	−1.60	0.29	3.56[a]	0.82

The AR measures are in percentages. Adj-BPM denotes the adjusted-BPM *t*-statistic. Wilcoxon test is the non-parametric signed rank T^{+} for the difference between the AR measures obtained under the OLS and GJR-GARCH estimations. [a], [b] and [c] denote statistical significance at a 1%, 5% and 10% level, respectively.

Under the OLS method, the CARs for mixed offers are positive and significant over the 2-day event-window $t-1$ to t whereas, for the GJR-GARCH-M method, the CARs are positive and significant over the 4-day window $t-2$ to $t+1$. The gains under the mixed payment method are larger than the gains under cash payments. Indeed, under the GJR-GARCH-M method, when mixed payment is made, the CAR over the entire 4-day event window is 2.247% compared with 1.770% over the entire 5-day event window when a cash payment is made. Heron and Lie (2002) do not find significant CARs for US acquirers that make stock or mixed offers. In contrast, Fuller et al. (2002) and Alexandridis et al. (2010) find negative and significant CARs for US acquirers that make stock and mixed offers.[9] Comparisons are difficult across prior studies. However, on balance we believe that the use of the F-F-C pricing factors and the GJR-GARCH-M estimation method is likely to lead to more reliable estimates of the CARs. The AR measures are also significantly different across estimation methods according to the Wilcoxon signed ranks test. As before, the AR measures are larger under the GJR-GARCH-M estimation method.

3.4.2 Targets and payment methods

We also examine whether the AR measures of targets are affected by the form of payment. If both acquirers and targets gain when a specific form of payment is used, this presumes that the market allocates the combined

[9] In general, empirical studies support the view that cash offers lead to positive and significant ARs for the shareholders of acquirer firms of most countries including the US, while share offers to lead to significant negative ARs (see also, Travlos, 1987; Draper and Puadyal, 2006; Faccio et al., 2006). Using monthly returns, Eckbo and Thorburn (2000) find positive and significant ARs for the acquirer firms for each of the payment methods we consider.

gains in some proportion to the economic contribution of each entity. Of course, this allocation of gains can reflect the perceived control, monitoring or other arrangements that the market expects shareholders of acquirers and targets to have over the joint entity.

Table 4b shows the AR measures for targets for each form of payment. The CARs are positive and significant over both estimation methods for all payment methods. However, there is strong variation in the span of the event-windows when the CARs are significant. For cash payments, the CARs under the OLS method are positive and significant for the 7-day event-window *t* –2 to *t* +4 whereas, the CARs are positive and significant over the 10-day event-window *t* –4 and *t* +5 under the GJR-GARCH-M method. For both estimation methods, the CARs for stock payments are positive and significant, but only for day *t*. The mixed payment method also generates positive and significant CARs. However, only day *t* is significant under the OLS method, whereas the CARs for the 7-day event window, *t*-3 to *t* +3 are significant under the GJR-GARCH-M method. Under the GJR-GARCH-M method, the overall gain from mixed payments is larger than the overall gain from cash payments even if the gain from cash payment arises over a larger event window. While the stock market allocates the gains to the merger across both acquirers and targets, the overall gains are always larger for target firms. So for mixed payments under the GJR-GARCH-M method, the CAR over the entire 3-day event window is 2.2471% for acquirers (see Table 3a, Panel C), whereas, the CAR for targets over the entire 7-day event window is 8.204% (see Table 3b, Panel C). So the market allocates 3.651 times (i.e., 8.204%/2.2471) more of the gains to target firms. This tendency for more of the gain to go to target shareholders holds for other forms of payment. As before, the Wilcoxon signed ranks test indicates that the AR measures are statistically different across estimation methods. The AR measures are larger under the GJR-GARCH-M method.

3.5 Capitalization value and liquidity

Moeller et al. (2004) show that small and large firms have different announcement returns that depend on size. The announcement returns for large firms are negative and insignificant whereas the announcement returns for small firms are positive and significant. The size effect is not affected by firm characteristics. There is also considerable evidence that stock liquidity impacts on the cross-section of returns (see, Pastor and Stambaugh, 2003; Liu, 2006). Following Pastor and Stambaugh (2003) liquidity as a priced factor can be considered to be compensation to investors who hold assets when there is the potential for negative shifts in their welfare as a result of holding such assets. In this case, average returns are predicted to be higher for stocks with high sensitivity to liquidity (see also Brennan and Subrahmanyam, 1996; Brennan, et al., 1998; Amihud, 2002). Liu (2006) also argues that small firms and firms with high bid-ask spread, high return and volume, are also less liquid. Since small stocks exhibit more sensitivity to liquidity than large stocks (see Pastor and Stambaugh, 2003), this means that liquidity is a state variable that is likely to complement our four-factor CAPM.

We use the trading volume of each stock to measure the impact of liquidity on the AR measures.[10] Eyssell and Arshadi (1993) find that trading volume increases prior to the merger announcements. This increase in trading volume can reflect the liquidity of the stocks. Ascioglu et al. (2002) also 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. We use the market capitalization value of each firm to capture the impact of size on the ARs. Prior studies show that the returns of portfolios made up of small stocks are largely unexplained (see Fama and French, 1996). So SMB may not fully capture the impact of size on the ARs. We test for the effects of size and liquidity by grouping the firms into three equal groups using, in turn, their market capitalization and trading volume. For these tests, we focus on GJR-GARCH-M estimation method rather than the OLS method due to the superior performance of the GJR-GARCH-M method.

3.5.1. Abnormal returns and market capitalization

Panel A of Table 5 shows the CARs according to the market

[10] Empirical studies employ several measures to capture liquidity. These include bid-ask spread, trading volume, price impacts of trading volume, amongst others (see Pastor and Stambaugh, 2003; Amihud and Mendelson, 1986; Amihud, 2002). Not all measures are reliable. Lee (1993) indicates that the bid-ask price does not contain the impacts of some large trades executed outside it while several small trades are executed within the bid-ask price thereby leading to bias.

capitalization of both targets and acquirers. As expected the largest gains are amongst targets. However, small acquirers and targets have the largest statistically significant gains and the gains decline as size increases such that there are no gains to large acquirers. Specifically, the positive CARs to small acquirers span the 9-day event window of *t* –6 to *t* +2 leading to an overall CAR of 7.752%. For medium acquirers, the significant CARs span the 3-day event window *t*-2 to *t*-1 and accumulate to 1.135%. As such, the overall significant CAR for small acquirers is 6.617 times (7.752/1.135) larger than the corresponding CAR for medium acquirers. Small acquirer shareholders are more likely to gain around merger announcements since managerial incentives are more likely to be aligned with those of their shareholders, and small acquirers suffer less from the hubris that affect large acquirers.

The above results are even stronger for targets. Small targets generate positive and significant Cars over the 18-day event-window *t* –7 to *t* +10.[11] This leads to an overall CAR of 9.240%. The CARs for medium targets are significant over the 10-day event window, *t* –2 to *t* +7. This leads to an overall CAR of 5.422%. The only significant CAR for large targets is at *t*, giving a gain 3.208%. So, large targets generate much smaller gains than medium or small targets. Large targets will generate smaller gains than medium or small targets if they are more likely to be acquired by large firms and the gains from synergy effects are small or trivial.

Notice that most of the gains to small and medium acquirers are over the pre-event period whereas most of the gains for small and medium targets are concentrated over the post-event period. Clearly, size impacts on the CARs of both acquirers and targets and its effect are greater for small acquirers and targets. The non-parametric Kruskal–Wallis test confirms that the CARs are statistically different across the groups and the largest gains are associated with small firms followed by medium firms.

[11] While out cut-off point spans ±21 days, the CARs beyond *t*+21 are also likely to be significant.

Table 5. Percentage CARs of acquirers and targets under the four-factor CAPM for the GJR-GARCH-M method by market capitalization and trading volume

	Acquirers							Targets						
Days	Small	*adj.* BMP	Medium	*adj.* BMP	Large	*adj.* BMP	Kruskal–Wallis test	Small	*adj.* BMP	Medium	*adj.* BMP	Large	*adj.* BMP	Kruskal–Wallis test
Panel A: Market capitalization														
–10	1.040	1.22	0.435	0.51	0.181	0.21	22.88[a]	0.021	–0.02	–0.144	0.12	–0.720	0.58	19.10[a]
–9	1.727	1.00	0.660	0.38	0.011	0.01	22.71[a]	0.071	0.05	–0.124	0.09	–0.845	0.05	19.87[a]
–8	2.731	0.27	0.772	0.08	–0.293	–0.03	27.25[a]	0.097	–0.05	–0.110	0.06	–0.977	0.51	17.06[a]
–7	3.390	1.26	1.004	0.37	–0.373	–0.14	25.87[a]	0.676	1.83[c]	0.178	0.48	–0.971	–0.26	16.13[a]
–6	3.951	1.89[c]	1.219	0.58	–0.505	–0.24	26.71[a]	0.706	1.78[c]	0.126	1.59	–1.089	–0.14	17.12[a]
–5	4.866	2.23[b]	1.400	0.96	–0.395	–0.36	25.94[a]	0.847	1.81[c]	0.228	1.62	–1.149	–0.82	16.96[a]
–4	5.651	3.09[a]	1.545	1.27	–0.509	–0.56	26.86[a]	1.033	2.32[b]	0.330	1.23	–1.161	–0.35	17.86[a]
–3	6.576	4.01[a]	2.028	1.85[c]	–0.238	–0.29	23.19[a]	1.112	2.10[b]	0.280	1.32	–1.335	–0.63	14.74[a]
–2	7.417	5.05[a]	2.428	2.48[b]	–0.096	–0.13	26.17[a]	1.631	2.23[b]	0.431	1.66[c]	–1.324	–0.14	16.40[a]
–1	8.346	5.24[a]	2.680	2.52[b]	–0.355	–0.45	27.36[a]	1.702	2.15[b]	0.461	1.89[c]	–1.332	–0.17	16.48[a]
0	1.213	2.51[b]	0.242	0.25	–0.297	–0.31	23.02[a]	4.751	4.82[a]	3.909	3.97[a]	3.208	2.00[b]	18.52[a]
1	1.066	2.30[b]	0.598	1.29	0.130	0.28	20.97[a]	1.696	2.43[b]	1.172	1.69[c]	0.430	0.71	15.61[a]
2	1.583	2.06[b]	0.735	1.42	–0.059	–0.11	23.60[a]	1.836	2.44[b]	1.238	1.70[c]	0.322	0.57	17.03[a]
3	1.879	1.33	0.615	0.44	–0.537	–0.38	21.74[a]	2.255	2.57[a]	1.341	1.78[c]	0.356	0.81	17.47[a]
4	2.400	0.84	0.590	0.21	–1.037	0.36	19.45[a]	2.429	2.58[a]	1.380	1.70[c]	0.358	0.76	16.85[a]
5	2.726	0.86	0.726	0.23	–1.106	–0.35	19.31[a]	2.381	2.53[b]	1.173	1.69[c]	–0.125	–0.27	16.74[a]
6	3.499	0.21	0.941	0.06	–1.295	–0.08	18.79[a]	2.882	3.18[a]	1.323	1.70[c]	–0.029	–0.06	16.55[a]
7	4.147	1.00	1.151	0.28	–1.196	–0.29	19.37[a]	2.998	2.46[b]	1.332	1.69[c]	–0.689	–1.13	15.82[a]
8	4.350	0.21	1.198	0.06	–1.240	–0.06	20.80[a]	2.955	2.38[b]	1.225	1.53	–1.033	–1.25	14.65[a]
9	4.751	1.01	1.300	0.55	–1.215	–0.52	19.24[a]	2.975	2.75[a]	1.240	1.55	–1.059	–1.47	14.30[a]
10	5.218	1.06	1.401	0.57	–1.435	–0.58	17.76[a]	2.884	2.93[a]	1.118	1.54	–1.287	–1.31	14.60[a]
Panel B: Trading volume														
–10	1.269	1.49	0.523	0.62	–0.136	–0.16	19.96[a]	–0.231	0.19	–0.280	0.23	–0.331	0.27	19.80[a]
–9	1.949	1.13	0.730	0.42	–0.282	–0.16	19.11[a]	–0.174	0.01	–0.328	0.02	–0.394	0.02	17.40[a]
–8	2.795	0.27	0.780	0.08	–0.365	–0.04	17.31[a]	–0.114	0.06	–0.342	0.18	–0.535	0.28	17.08[a]
–7	3.249	1.21	1.049	0.39	–0.278	–0.10	21.04[a]	0.375	0.76	–0.051	–1.38	–0.442	–0.24	18.30[a]

–6	3.940	1.89^{c}	1.119	0.54	–0.394	–0.19	21.58^{a}	0.346	0.87	–0.096	–1.21	–0.507	–0.32	19.74^{a}
–5	4.902	2.25^{b}	1.467	1.35	–0.498	–0.46	23.56^{a}	0.518	1.20	–0.013	–0.93	–0.580	–0.72	19.89^{a}
–4	5.648	3.09^{a}	1.705	1.86^{c}	–0.666	–0.73	24.15^{a}	0.662	1.73^{c}	0.083	2.48^{b}	–0.544	–0.81	19.05^{a}
–3	6.572	4.00^{a}	2.221	2.71^{a}	–0.426	–0.52	19.82^{a}	0.821	1.94^{c}	0.115	5.44^{a}	–0.879	–1.14	18.02^{a}
–2	7.412	5.05^{a}	2.649	3.61^{a}	–0.311	–0.42	19.58^{a}	1.342	2.07^{b}	0.283	2.91^{a}	–0.887	–0.91	17.34^{a}
–1	8.159	5.12^{a}	2.759	3.47^{a}	–0.247	–0.31	20.47^{a}	1.496	2.12^{b}	0.303	3.82^{a}	–0.967	–1.22	16.87^{a}
0	1.099	2.27^{b}	0.433	0.45	–0.374	–0.39	18.27^{a}	4.756	4.83^{a}	4.319	4.39^{a}	2.793	2.84^{a}	15.99^{a}
1	1.104	2.38^{b}	0.503	1.09	0.188	0.41	18.99^{a}	1.453	2.08^{b}	1.084	1.78^{c}	0.760	1.25	19.93^{a}
2	1.418	2.73^{a}	0.762	1.47	0.080	0.15	16.29^{a}	1.615	2.15^{b}	1.104	1.71^{c}	0.677	1.20	16.20^{a}
3	1.442	1.02	0.620	0.44	–0.106	–0.08	17.74^{a}	1.928	2.20^{b}	1.284	1.92^{c}	0.739	1.48	15.33^{a}
4	1.471	0.51	0.709	0.25	–0.227	0.08	19.14^{a}	2.035	2.16^{b}	1.356	1.89^{c}	0.776	1.64	17.37^{a}
5	1.933	0.61	0.914	0.29	–0.501	–0.16	17.80^{a}	2.006	2.13^{b}	1.103	1.80^{c}	0.320	0.68	16.52^{a}
6	2.822	0.17	1.062	0.06	–0.740	–0.04	17.23^{a}	2.569	2.83^{a}	1.236	1.79^{c}	0.371	0.82	15.25^{a}
7	3.336	0.80	1.423	0.34	–0.658	–0.16	16.38^{a}	2.669	2.19^{b}	1.160	1.67^{c}	–0.187	–0.31	15.42^{a}
8	3.554	0.17	1.449	0.07	–0.695	–0.03	15.98^{a}	2.613	2.11^{b}	1.021	1.44	–0.488	–0.79	15.01^{a}
9	3.900	1.24	1.663	0.71	–0.727	–0.31	18.05^{a}	2.733	2.53^{b}	1.031	1.67^{c}	–0.609	–1.13	16.38^{a}
10	4.280	1.30	1.936	0.79	–1.032	–0.42	19.52^{a}	2.716	2.76^{a}	0.972	1.73^{c}	–0.974	–0.99	14.76^{a}

Adj-BPM denotes the adjusted-BPM t-statistic. K-W test denotes the Kruskal-Wallis test. ^{a}, ^{b} and ^{c} denote significance at a 1%, 5% and 10% level, respectively.

3.5.2. Abnormal returns and liquidity

Panel B of Table 5 also shows the CARs when the firms are grouped according to the magnitude of their trading volume – our measure of liquidity. The results here mirror those based on the capitalization value of the firms. Small acquirers and targets generate the largest positive and significant CARs over a larger event-window, followed by the medium acquirer and target firms. The CARs for large acquirers are not significant, whereas only the positive CAR at *t* is significant for large targets. As before, the significant CARs for acquirers span a shorter event window than, those of small targets. As such, the significant CARs for small acquirers span the 9-day event-window *t* –6 to *t* +2, whereas for small targets, the event window spans 15-days. The overall CARs across these event windows are 7.427% for small acquirers and 8.450% for small targets. Lee and Chung (2013) also find that US targets with less liquid stocks benefit from larger ARs. The Kruskal–Wallis test confirms that the CARs are significantly different according to the magnitude of the trading volume. If low trade volume represents low liquidity, then most of the gains associated with merger announcements occur for stocks with low liquidity.

4 Conclusions

We examine the ARs surrounding the merger announcements of US-listed firms. We estimate a four-factor CAPM to capture the cross-sectional variation in daily stock returns under both the standard OLS and GJR-GARCH-M estimation methods. We find that shareholders of both acquirers and targets gain as a whole around the merger announcements but the gains to acquirers only arise when the CARs are estimated using the GJR-GARCH-M method. We hypothesize that M&As increase efficiency and that the gains to shareholders at merger and acquisition announcement truthfully suggest enhanced prospects of future cash flow performance. So the estimation methods affect the significance of the results and in turn the statistical inferences regarding the gains around merger announcements. We attribute the GJR-GARCH-M results to the ability of this estimation method to capture both the conditional volatility and asymmetric effects in the excess returns. These effects will be particularly pronounced when daily returns are used and when the event induced variance is strongest. The OLS method will perform less well under those conditions. Cash and mixed payment methods also generate positive and significant CARs for both targets and acquirers. The mixed payment method generates the largest gains over the event-window. These results hold under both estimation methods but the GJR-GARCH-M method always generates superior results. The CARs are not significant for either acquirers or targets when stock payments are made. So it appears that investors do not value the premium associated with the over-valued stocks of acquirers (see Myers and Majluf, 1984). Again, the research findings of a negative return in the acquiring firm stock prices following M&A announcements would infer that the gains from M&As are exaggerated. Small-capitalization stocks and stocks with low liquidity generate the largest CARs for both acquirers and targets. These gains span up to 18 days for targets based on capitalization value and 15 days based on trading volume. Large capitalization and volume acquirers generate insignificant CARs whereas large capitalization and volume targets generate positive CARs only at day *t*. Large acquirers and targets will generate little or no gains to their shareholders if there is little room for exploiting synergistic effects. Similarly, large acquirers and target interests are less likely to be aligned with the interests of their shareholders. This factor can give rise to insignificant CARs for acquirers and targets. Our overall results strongly support the view that the ARs are affected by the choice of CAPM and the estimation method. These factors impact the ARs in addition to the usual financial characteristics of targets and acquirers. Since the firms making these losses are mostly acquirers, management of acquiring firms need to adopt a new investment strategy that can earn economic returns, which possibly would not be too shocking in an efficient capital market. Our preferred estimation method is the GJR-GARCH-M method as it generates more consistent results. We suggest that future research should be looking at an examination of conditional CARs, and the inclusion of additional control variables that are known to affect abnormal returns around M&As announcements, such as deal characteristics, firm characteristics, and industry characteristics).

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