UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Anticipation of Takeover Transactions by Shifts in the Correlations: Evidence from the U.S. Takeover Market

Mohammad Irani

Graduate School

Master of Science in Finance
Master Degree Project No. 2011:151
Supervisor: Martin Holmén

This work is dedicated to my family.
For their love, caring and support

Table of Contents

Acknowledgements

I would like to express my gratitude to my supervisor, Martin Holmén, for his inspiration, encouragement, guidance and support from the initial to the final level of this thesis. He provided constructive comments and helpful suggestions which did not only improve the quality of this thesis but also taught me how to address a research issue in practice. He was so patient and his office door was always open to my queries.

I would like to thank specially Joakim Westerlund for constructive suggestions about the econometric part of this paper. I learnt the very essential econometric concepts to conduct this research by attending his Financial Econometrics and Applied Econometrics courses.

I would also like to thank Taylan Mavruk for his helpful comments on the earlier draft of this paper and his interest in my work.

This paper is part of two-year M.Sc. program in Finance at School of Business, Economics and Law, University of Gothenburg. I would therefore like to thank the Administration Office at the Graduate School for their kind support, making my stay in Gothenburg, Sweden memorable and enjoyable.

Finally, I am solely responsible for any errors that this thesis may contain.

May 2011

Anticipation of Takeover Transactions by Shifts in the Correlations: Evidence from the U.S. Takeover Market

Mohammad Irani
May 2011

Abstract

This paper provides a new solution for the bidder unpredictability dilemma in takeover acquisitions. The sample encompasses 125 successful acquisitions between non-financial exchange-listed U.S. companies from 2003 to 2006. A break in the mean of correlations between the target and the acquirer daily stock returns is detected on average **54** trading days *before* the announcement in 84% of the sample, which suggests that the market *anticipates* the pair-firms in bid offers. Another break is observed on average **19** days *after* the announcement in 77% of the sample. This indicates that the market not only *reacts* to the public bid announcements but also increases the likelihood that the bidders will successfully acquire the target firms. There is no evidence that the market is able to anticipate the payment form. The empirical evidence is furthermore provided for the predictors of the likelihood of observing the anticipation and the reaction breaks and for the determinants of the number of breaks per deal. Among those predictors, pair-firms from a similar industry and *Cash* offers are the most economically significant regressors in predicting the bid offers (and the number of breaks per deal) and the reaction to the bid announcements, respectively.

Keywords: Acquisitions; Anticipation; Payment form; Structural breaks; Unconditional correlations
JEL Classification: G34

1. Introduction

The target shareholders gain a substantial premium at the announcement of the takeover transactions as they hold most of the bargaining power (Grossman et al (1980)). Schwert (1996) observes that the premium to the target shareholders is not only limited to the markup period (the post-announcement period) but the stock returns indeed begins to run up on average 42 trading days prior to the initial public announcement of the bid. In a recent Mergers and Acquisitions survey, Martynova et al (2008) show that most researchers detect a significant run-up premium between 13.3% and 21.8% to the target shareholders during a period of one month prior to the bid announcement. The observed pre-announcement abnormal returns indicate that the market can **anticipate** the target firms that are subject to takeover offers. Conversely, earlier investigations are mostly unable to demonstrate any significant abnormal gains to the bidder shareholders in the run-up period (e.g., Martynova et al (2008)).[1] This trivial run-up premium to the bidder shareholders implies that the market is generally unsuccessful in predicting the acquirer until the public announcement of bid offers. Furthermore, most of M&A studies find that post-announcement cumulative abnormal returns (i.e., mark-up premium) to the acquirers are almost insignificant (e.g., Schwert (1996)).Therefore, it is difficult to estimate whether the market is able to predict bidders.

A possible solution to the bidder unpredictability dilemma is to use dynamic correlations between the target and the bidder stock returns prior and subsequent to the announcement day. While the returns to the acquirers are approximately smooth around the announcement day, returns to the target shareholders rise both prior and subsequent to the announcement day (run-up and mark-up premiums). This divergence between returns to the target and acquirer stocks can increase the likelihood of observing break(s) in the join distributions of returns to the pair-firms (i.e., break(s) in the mean of return correlations) around the announcement day. Therefore, the unconditional dynamic correlations which measure the time-varying co-movements in the return series to pair-firms are utilized in this study. The existence of pre-announcement shift(s) in the mean of return correlations is interpreted as the anticipation of a takeover offer and its pair-firms by the market.

The **aim** of this paper is to investigate whether the market can anticipate the target and acquirer pairs in the successful takeover transactions by addressing the following **research questions**:

First, Whether there is (are) structural break(s) in the unconditional mean of correlations between the target and the acquirer daily stock returns prior and subsequent to the announcement of the initial bid offer and how do these correlations evolve through time?

Second, what are the empirical determinants of the number of breaks per deal and the likelihood of observing pre- and (or) post-announcement shifts in the unconditional mean of correlations?

The pre-announcement breaks is of vital importance as they reveal how the market can anticipate the pair-firms in takeover transactions while there is no public information about the deals and contract terms. The presence of post-announcement shift in the correlation is useful in understanding how the

---

[1] Martynova et al (2008) summarize the results of 65 M&A studies in which the one-month Cumulative Average Abnormal Returns (CARRs) to the bidder shareholders prior to the initial bid offer are generally insignificant. And this result is interestingly robust to the use of sample data from various merger waves in different countries.

market reacts to the public bid announcements and whether these shifts can provide any relevant information about the probability that the target will be successfully acquired by the bidder. However, the post-announcement case is less compatible with the anticipation goal of this study compared to the case of multiple pre-announcement breaks.

According to Ismail et al (2010), the Equity offers are frequently observable when the acquirer and target firms are very much alike. If the market predicts that the bid offer is successfully consummated, announcing an *Equity* offer therefore causes the stock returns to these firms to fluctuate almost identically at post-announcement period as these firms are going to be merged and presented as one entity in the market. Thus, it is expected that the announcement of *Equity* or *Mixed*-payment (i.e., a combination of *Equity* and *Cash* payment) offers raises the correlations dramatically, and so there might be structural break toward perfect correlation after the announcement. On the other hand, determining the dollar value of target shares in *Cash* offers can generally cause the stock returns of target shares to become almost flat at the post-announcement period, and so the related return volatilities drops dramatically. As argued by Anderson et al (2001), the fall in the return volatility of target share decreases the return correlations in *Cash* offers at the post-announcement period.[2] In contrast to the *Equity* or *Mixed*-payment offers, it is expected that announcing a bid offer with all payment in cash shifts the returns to the target and acquirer stocks towards non-correlation (i.e., independent return series).

DataStream and Zephyr databases are used to collect adjusted daily-closed prices and the information about the successful M&A deals of public firms involved in the US take-over transactions for the period of 2003 to 2006, respectively. The Simple Moving Average method (with a rolling window of 21-trading-day) is employed to model the unconditional non-stationary aspect of the return correlations. In a recent work, Chiang & Li (2009) also use daily returns to construct rolling monthly realized correlations between the stock and bond markets.[3] Then the Structural Breaks (SB) methodology developed by Bai and Perron (1998, 2003a, 2003b and 2006) is implemented to examine the existence of shift(s) in the mean of unconditional correlations between the acquirer and target returns around the announcement day. The Probit and Poisson regressions are also estimated to investigate empirically the predictors of probability of observing the pre- and post-announcement breaks and the determinants of number of breaks per deal, respectively.

This paper will contribute to the Finance literature (particularly, the M&A literature) along at least five dimensions. First, while previous studies are unsuccessful in predicting acquirers at pre-announcement period, the novel application of multiple shifts in the mean of correlations in this paper discloses how the market anticipates the pair-firms and bid offers in takeover transactions. Moreover, the results indicate that the market reacts not only to the public bid announcements but also predicts the delisting of target firms due to the successful acquisitions. However, the market is unable to anticipate the payment form at the pre-announcement period. Second, this study explores the relation between the probability of observing multiple shifts in the mean of correlations around

---

[2] They find that the realized correlation between a pair of individual stocks is low (high) when their realized volatilities are also low (high).

[3] Moreover ,this approach is directly in line with the earlier works by French et al (1987), Schwert (1989, 1990a, b), Schwert and Seguin (1991) and Campbell et al (2001),who compute the monthly realized stock based on daily return observations within each month. See Foster and Nelson (1996) and references therein for the discussion about the asymptotic property of the rolling sample estimates.

the announcement of bid offers and the target, acquirer and deal characteristics. Third, the existence of multiple shifts in the mean of correlations around the announcement of successful acquisitions proposes several questions for further research which will be discussed later in the conclusion section. Fourth, while there are several studies about non-stationarity in the unconditional volatilities, this study will be among the pioneers that show non-stationarity in unconditional correlations. Finally, since increasing (decreasing) correlations among the pair stocks imply that the benefits of portfolio diversification have decreased (increased) over time, the observed dynamic correlations has practical implications for portfolio managers who can rebalance their portfolios based on the timing and magnitude of shifts in the mean of return correlations.

The rest of paper is organized as follows: Section 2 demonstrates a case study for multiple shifts in the rolling correlations and Section 3 reviews the relevant literature on the correlations, Section 4 presents the methodology and Section 5 explains data and descriptive statistics. Section 6 presents the empirical results and Section 7 discusses several robustness tests and finally Section 8 concludes and provides some suggestions for further research.

2. A Case of Multiple Shifts in the Rolling Correlations

Results of performing structural break analysis for a sample takeover transaction is presented in this section in order to provide insights about the proposed approach to study how the market can anticipate a bid offer. However, theoretical discussions about the adequacy of methods, data and results for the main sample will be introduced in the next sections.

Conexant Systems Inc. acquired all stake of GlobeSpanVirata Inc. in a stock swap transaction (i.e., merger) valued at $933.32 million USD[4]. The deal announced on the 3 December 2003 and consummated with delisting of GlobeSpanVirata‘s stocks on 17 February 2004(i.e., 84 trading days after the announcement day (=0)).

Figure 1 presents daily log-returns to the target and acquirer’s stocks. The number of daily log-returns prior to the announcement day (222 trading days) is determined in such a way that approximately 30% of total daily correlation located after the announcement day as this study mainly focuses on the examination of multiple shifts in correlations prior to the announcement day (i.e., anticipation break). Although the announcement return to the target shareholders was insignificant (-0.7%), they gained a substantial profit (36.7%) in the post-announcement period (the period between the announcement and delisting of target).[5] The return to the acquirer shareholders at the

[4] This deal seems to be a vertical merger since the primary industry of Conexant Systems Inc is semiconductors while GlobeSpanVirata Inc. has been classified as a designer of Computer integrated systems.
[5] In fact, this sample deal is selected in such a way that the outlying effect of announcement returns is much smaller compared to a typical deal in the sample in which there is a significant positive (negative) announcement return to the target(acquirer) shareholders . This case is thus chosen to avoid any complexity required to deal with outlying announcement returns in this stage of the paper. However, the effect of outliers and why they should be controlled (i.e., excluded from the daily log-return series) in the analysis of this paper will be discussed in more detail in section 5.

announcement day dropped dramatically (-11.4%) which was compensated later in the post-announcement period (23%).[6]

The Simple Moving Average (SMA) method is used to model time-varying correlations. Rolling correlations with a window of 21-trading-days explains why the correlation series commences at day -202 while the log-return series starts at day -222. First, it is obvious from Figure 1 that the correlation series, contrary to the stationary assumption of event study methodology, is time varying and the major shift(s) in its mean is apparent around the announcement of bid offer (day 0) .Second , whenever the log-returns are highly volatile , the rolling correlations are low, and vice versa. Lower correlations are also evident when the magnitude of log-returns are incomparable and (or) when the log-returns do not fluctuate in the same direction.

The daily log-returns and its rolling correlations can be divided to three different regimes in Figure 1. The first segment is from day -222 to day -57 where both return series are noticeably volatile. In this regime, average daily log-returns to the acquirers are much larger than of that to the target shareholders (0.76% compared to 0.24%) and both log-returns series do not fluctuate in the same direction for non-negligible days. And, in turn, the related rolling correlations compared to other regimes are on average smaller, more volatile. The second regime covers the announcement day and it is between day -56 and day 6 in which the log-returns compared to that first segment are much less volatile and smaller in size. However, the acquirer's log-returns is again on average greater than the returns to the target's stock (0.07% and -0.18% respectively). In this regime, the rolling correlations are on average less volatile than correlation in the first segment, so returns to both firms are on average more correlated. This change in the average correlations points out a higher likelihood of observing a shift in the mean of correlations around day -57. In the third regime, from day 7 until delisting of target 's stock at day 84, both return series oscillate almost identically which explains why the returns to both shareholders converge to prefect correlation after the day 22. This dramatic change leads to a predicted existence of a break in average daily correlations around day 22.

The Bai and Perron's (henceforward, referred as to the BP) multiple structural break methodology (SBM) is used to investigate statistically the claims about the existence of breaks in the return correlations around day -57 and day 22 in this sample. Their SB test shows that the there are two shifts in the mean of correlations corresponding to day -53 and day 20 at 1% significance level. The dot line in Figure 1 illustrates that the average daily rolling correlations based on the estimated break dates are equal to 0.37, 0.6 and 0.95 in the subsequent regimes. The results of structural break analysis are thus consistent with the expectations about the break dates and the magnitude of shift in the mean of daily SMA correlations in *Equity* offers.

The existence of a break at day -53 suggests that the market can anticipate the bid offer prior to the announcement day. It seems that for this sample market also surprisingly predicts the payment form (i.e., *Equity* offer) as the shift in the mean of correlations prior to the announcement day is upward

[6] This significant positive return to the acquirer's stock is odd as the most of studies report insignificant or slightly negative returns on average to the acquirers at the post-announcement period. However, a comparison with the S&P 500 index reveals that this abnormal increase in share prices is due to the general economic recovery in the market after IT bubble.

(i.e., 0.6-0.37=0.23). [7] This fact can be simply explained, for this case, by the significant return to the acquirer in the regime 1 which is consistent with asymmetric information hypothesis that the acquirer offers its share when they are overvalued in takeover transactions (see, for example, Shleifer and Vishny (2003)). As expected, the market reacts to the public announcement of an equity swap transaction as the correlation series shifts towards perfect-correlations at day 22. This upward shift in the mean of correlations at day 22 due to the merging offer suggests that the market anticipates the successful acquisition of target by the acquirer almost three months prior to the delisting of target shares at day 84.

As hypothesized early and showed in this case, variation in the mean and (or) volatility of daily log-return series to the target and acquirer shareholders around the announcement day is the key driver of structural breaks in the daily rolling correlations. This fact motivates to conclude that the individual return distribution to each of the pair-firms might be also subject to multiple shifts. On the contrary, the results of SB tests point out that there are shifts *only* in the distribution of returns to the acquiring firms, and so shifts in both of individual return distributions is not a valid assumption in this case for explaining the shifts in the mean of rolling correlation[8]. This suggests the merit of the proposed approach (i.e., shifts in the correlations) compared to the well-known event study method in predicting pair-firms in takeover transactions. The reason for this claim is that the proposed approach is based on breaks in the *joint* distribution of returns while the event study methodology uses the *disjointedly* return distributions to predict each of the target and bidder firms. However, the systematic comparison of these methods is out of the scope of this paper and left for further research.

3. Relevant Literature on the Correlations

There are only few studies that use the return correlations in the M&A literature, nonetheless, those investigations use completely different methodologies to address different hypotheses compared to this study. For instance, Ismail et al (2010) observe that, besides the common determinants, the point estimate of return correlation between the target and the acquirer has a significant power in explaining the method of payment in the M&A transactions. They find particularly that firms with high correlation tend to use shares and firms with low correlation are often offered cash in the takeover transactions. In another study, Morellec et al (2005) construct a theoretical model in which the returns to the target and the acquiring firms can be predicted by using the point estimate of correlation between the bidder and the target stock returns. However, Ismail et al (2010) could not confirm empirically this theoretical prediction in their sample. These empirical studies are based on the event study methodology which assumes that the second-order moments (the volatilities and the correlations) are stationary in the sample period. On the other hand, by using the SMA method for daily and monthly returns over the period 1926 through 1997, Campbell et al (2001) prove empirically that not only the realized volatilities of the market but the industry and idiosyncratic firm level moments are also time-varying. In that period, different variation rate of volatilities among

[7] In fact , the mean *t*-tests show that the daily log-returns to the acquirers in regime 1 are only significant among all average daily log-returns for both of firms in the three regimes. The t-tests for difference in average daily correlations through subsequent regimes indicate that neither of them is significant.
[8] The multiple shifts is occurred at two days(day -169 and day -80) and the mean of daily returns is only significant (i.e., 19.57%) in the second regime.

individual stocks leads all pair-wise correlations to vary over time. On the whole, the assumption that the distribution of returns (volatilities and correlations) is stationary over time is usually invalid and the dynamic method is therefore considered to be relevant in modeling the correlations in this paper to avoid any misleading results.

There are several dynamic models developed in the econometric literature to estimate the volatility and correlation of the underlying returns. Among various methods listed in Andersen et al (2006), the Realized Volatility, the Implied Volatility and the Stochastic Volatility methods are not applicable in this study due to the limitation on access to high-frequency intra-daily data, the very limited number of products whose prices depend on the correlation between two assets and the binding distributional assumptions of constant and mean reverting second-order moments, respectively. The relevant methods to capture the dynamic feature of return correlations in this study are the SMA (Simple Moving Average) model and the Multivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) class of models.

The most appropriate model for the purpose of this paper is the SMA approach due to the following reasons. First, the Monte Carlo simulation results of De Santis et al (2003) indicate importantly that the probability that the observed sample of return series is drawn from a single distribution is statistically trivial. Thus, the time-variation in the data generating process is the key driver of the observed dynamics in the second-order moments. Moreover, their simulation analysis points out the merit of the SMA method to capture the dynamic feature of the second-order moments of return series. Second, which is directly the consequence of the first reason; the unconditional covariance stationary assumption of conditional parametric GARCH-type models is mostly invalid (as there are shifts in the unconditional variance series) and can lead to biased estimates of the second-order sample moments (e.g., Mikosch and *Stărică* , 2004a and 2004b).[9] Mikosch and *Stărică* (2004b) argue that the assumption of unconditional covariance stationarity is too strict and too simplistic in GARCH class of models and conclude that the significant part in modeling dynamics of log-return series is the changes in the unconditional variances and correlations. Therefore, the non-parametric SMA model which treats sample moments as observable variables and provides model-free unbiased estimates of the ex-post realized correlations are preferable to those parametric GARCH models. The SMA estimation procedure is not based on any distributional assumption, and so it is free of any model building discrepancies. The SMA method is thus applied in this study to construct time-varying correlations.

It is very likely to observe structural breaks in the unconditional correlations due to the abovementioned time-variation in the joint distribution of returns to the pair-firms. Therefore, the Structural Breaks methodology developed by Bai and Perron (1998, 2003a, 2003b and 2006) is used to examine the existence of shifts in the mean of correlations around the bid announcements. The use of SBM to detect shifts in the correlations is somehow similar to the work by McMillan & Ruiz (2009), who use the BP methodology to show that the mean of *unconditional variance* of 10 equity indices are subject to multiple structural breaks. However, they use the conditional Fractional GARCH method for estimating the mean of the variance (absolute returns) which is less proper (as

9 The biased estimates of the GARCH models are further observed by Figlewski (1997), *Stărică* and Granger (2005), Herzel et al (2005) and McMillan & Ruiz (2009) among others.

discussed) compared to the unconditional SMA approach. Moreover, the use of SBM after constructing the SMA correlations can extract any slow moving trend without disturbing the general pattern of the data.

Overall, the SMA model is initially applied to estimate daily unconditional correlations between the returns to the acquirer and the target shareholders of each M&A deal in the sample and then the SB methodology is finally utilized to examine the potential breaks in the mean of unconditional correlations prior and subsequent to the bid announcement in this paper.

4. Methodology

Since daily stock prices are often non-stationary (i.e., they have unit roots), the correlations based on the price are not the appropriate statistic to describe the co-movements in the acquirer and the target series. Thus, the log returns ($r = \ln(\frac{p_t}{p_{t-1}})$ with p_t and p_{t-1} are the adjusted closing prices at day t and t-1, respectively) of the acquirer and the target firms are used to construct the correlation coefficients. Another advantage of using log returns (henceforth, referred as to the returns) is, as argued by Andersen et al (2001a), that their realized unconditional correlations are almost normally distributed.

Since the variances and correlations of the target and the acquirer stock returns are expected to evolve through time (especially prior and subsequent to the announcement date), as argued by De Santis et al (2003), use of high-frequency data on short horizons can improve the accuracy of second-order moment estimates. [10] The reason is that the likelihood of observing returns from the same volatility and correlation regime increased. Therefore, daily returns of the firms in the M&A deals are used to construct the dynamic correlations in this study.

4.1. The Simple Moving Average (SMA) Method

The Simple Moving Average method with a fixed rolling window is used in this paper to derive time-varying correlation coefficients for returns on those two firms that participates in the M&A deal. Using a relatively small window in the SMA rolls reduces the bias related to the use of more old data in the window (i.e., large window) which may contain relatively little information about the current state of the system but it increase the variance of SMA estimates. However, the small window increases the likelihood that the returns are generated by the same distribution, i.e., that the returns are almost identically distributed. The mixed distribution probability increases if a larger window is used as more daily returns from the pre-announcement period (or from the previous regime) is used to construct the post-announcement correlations(or the current regime correlations). Thus, using the SMA approach with a small rolling window can ensure more the identical and independent distribution of daily returns and consequently generate less biased estimates of unconditional daily correlations.

[10] See Merton (1980) for discussion about this result.

The SMA correlations are calculated each day via the previous 21 daily returns to the pair-firms (i.e., at each point in time, the window contains approximately daily returns of the most recent month). Each day, the SMA estimate is updated by adding the most recent return observations and deleting the observations that are now 22 days old. Figlewski (1997) and McMillan and Speight (2004) argues that the market practitioners rely only on the last 30 to 60 days in computing the historical moments, hence the use of last month returns as the rolling window in computing the unconditional correlations is consistent with the practitioners approach. Moreover, the 21-trading-day correlations approach is in line with the work by Chiang & Li (2009), who rely on daily return observations for the construction of rolling monthly realized volatilities and correlations between the stock and bond markets, and earlier studies by French et al (1987), Schwert (1989, 1990a, b), Schwert and Seguin (1991) and Campbell et al (2001) ,who compute the monthly realized stock volatilities based on daily return observations within each month. The SMA approach for calculating time-varying correlation coefficients is defined as:

$$\hat{\rho}_{actg,t} = \frac{\sum_{j=t-20}^{t}(r_{ac,j}-\bar{r}_{ac})(r_{tg,j}-\bar{r}_{tg})}{\sqrt{\left(\sum_{j=t-20}^{t}(r_{ac,j}-\bar{r}_{ac})^2\right)\left(\sum_{j=t-20}^{t}(r_{tg,j}-\bar{r}_{tg})^2\right)}} , \qquad t = -N, -N+1 , \ldots , 0 , 1 , \ldots , C \qquad (1)$$

Where $\hat{\rho}_{actg,t}$ is the unconditional correlation coefficient between the most recent 21 daily returns to the acquirer and the target firms at day *t* , *t* is daily subscript in which *–N* , *0 and C* stand for *N* days prior to the announcement date, the announcement day(or the reference date) of the M&A deal and the consummation day(i.e., *C* days after the announcement day) of the successful takeover transaction, respectively. $r_{ac,j}$ and $r_{tg,j}$ represent the returns to the acquirer and target shareholder at day j, correspondingly . The sample mean return of the acquirer and the target firms for the return observations from days *t-20 to t* is denoted by $\bar{r}_{ac}$ and $\bar{r}_{tg}$, respectively.

Figlewski (1997) argues that the sample mean of daily returns (here, $\bar{r}_{ac}$ and $\bar{r}_{tg}$) is highly imprecise approximation for the true mean except for very long samples. He suggests computing the sample second-order moments around zero (i.e., imposing a "mean" of zero) rather than the inaccurate sample mean. Moreover, Jorion (1995) notes that the "With daily data, the average term $E(r^2)$ dominates the term $[E(r)]^2$ by a typical factor of 700 to one. Therefore, ignoring expected returns is unlikely to cause a perceptible bias in the volatility estimate." So a "mean" of zero for return series is used in this paper to determine the unconditional correlations rather than the imprecise sample mean which is computed only from the most recent 21 daily returns. After adjusting the mean of returns and identifying the size of the rolling window, the corresponding SMA correlation series is given by:

$$\hat{\rho}_{actg,t} = \frac{\sum_{j=t-20}^{t} r_{ac,j} r_{tg,j}}{\sqrt{\left(\sum_{j=t-20}^{t} r_{ac,j}^2\right)\left(\sum_{j=t-20}^{t} r_{tg,j}^2)\right)}} \qquad (2)$$

The equally weighted scheme of the SMA method can produce biased estimates if there is (are) outlier(s) in the sample of returns. Each outlier can provide a series of biased estimates since its effect lasts for as many windows as use this influential observation. Moreover, the abrupt jumps can be observed in the SMA estimates after the disappearance of those outliers from the rolling windows. Therefore, the potential outliers need to be identified and controlled before influencing the SMA estimates of correlations.

4.2. The Structural Break Methodology (SBM)

The application of Bai and Perron 's SBM to detect multiple shifts in the return correlations is particularly appropriate in this paper as it estimates multiple structural breaks at unknown dates by minimizing the global sum of squared residuals.[11] The BP's dynamic programming algorithm determines the candidate break dates and regimes in which the OLS parameters and associated residuals can be consequently obtained. The break date tests are designed in such a way that they can tolerate the heterogeneity in the distribution of regressors (i.e., correlations, here) and residuals across regimes. This heterogeneity feature makes the BP method competent for the hypotheses of this study as it is expected that the distribution of unconditional return correlations are subject to change prior and (or) subsequent to the bid announcement which can subsequently lead to structural breaks in the mean of correlations.

The main aim of this study is to identify the number of breaks (i.e., *m*), the break dates and corresponding shifts in the mean of correlations per deal by estimating the following regression:

$$\hat{\rho}_{actg,t} = \bar{\rho}_{actg,i} + \varepsilon_t \qquad t = T_{i-1} + 1 , . . . , T_i \qquad (3)$$

For $i = 1 , . . . , m+1$, where the $\hat{\rho}_{actg,t}$ is the estimate of unconditional return correlation of the acquirer and the target firms at day t obtained from the SMA method, $\bar{\rho}_{actg,i}$ ($i=1, . . . , m+1$) is the mean estimates of unconditional return correlation between the acquirer and the target firms in the i^{th} regime and ε_t is the disturbance at day t. The indices $T_1 , . . . , T_m$ are the estimates of unknown break dates for the different regimes and $T_0 = -N$ denotes N days prior to the announcement date and $T_{m+1} = C$ refers to the consummation day of the takeover transaction at the post-announcement period.

The practical recommendations of Bai and Perron ((2003a, 2006)) are applied in this paper to improve the size and power of the structural break tests in estimating the number of shifts in each correlation series. First, the statistical significance of $UD \max F_T$ test is used to investigate the presence of at least one break ($m=1$) in the mean of unconditional correlations.[12] Second, BP suggest

---

[11] For further details about the Bai and Perron's Multiple Structural Break Methodology, see Bai and Perron (1998, 2003a, 2003b and 2006).

[12] This double maximum test is based on the *Sup F-type* tests for the null of no break against the alternative of unknown number of breaks given the upper bound for the number of breaks determined by the researcher (Bai and Perron, 1998).

that the $SupF_T(\ell+1|\ell)$ test is applied sequentially by using the sequential estimates of the break dates to assess whether there are more than one (*m > 1*) breaks or not. This sequential approach implies that the number of breaks is equal to *m* when for the first time the $SupF_T(m+1|m)$ test statistics becomes insignificant at conventional significance levels. As BP claim this testing process is useful to consistently estimate the number of structural breaks since it allows the specific to general modeling strategy. Finally, the detected *m* together with the break dates are used to estimate the equation (3) and its parameters, the mean of return correlations across segments ($\bar{\rho}_{actg,i}$).

Bai and Perron (1998) argue that the asymptotic distribution of these test statistics rely on the trimming factor which consequently determine the minimum distance between subsequent break dates. Although the trimming factor (which is denoted by ε and measured as the percentage of the whole sample observations) can be also specified by the user, BP (2006) assess the size and power adequacy of structural break tests via simulation analysis and conclude that a higher trimming factor (i.e., $\varepsilon \geq 15\%$ for a typical sample with more than 100 observations) should be selected when one wishes to allow for the heterogeneity in the data(correlations, here) and errors across segments and (or) for the heterogeneity and the autocorrelation in the residuals. However, they suggest that a smaller ε can also be used if the sample size is large enough or if some of those heterogeneity options are not chosen. Since it is likely that the unconditional SMA return correlations are serially correlated and it is quite probable to observe heterogeneous distribution of correlations and residuals across segments (especially around the announcement day), a trimming factor of 15% is selected which is more suitable for constructing of break tests in this paper. The trimming factor determines the maximum number of breaks (*b*) that the researcher can choose and maximum five break points are allowed for a trimming factor of 15%. Since it is quite likely that there are several shifts in the mean of correlations prior and subsequent to the announcement date, the maximum of 5 breaks per deal (i.e., *b*=5) is selected. Otherwise, imposing a smaller number of breaks would restrict the analysis in this study. This trimming factor ($\varepsilon = 15\%$) indicates that at least 15% of return correlations should exist after the announcement date, otherwise the BP method will push all the potential breaks prior to the announcement date of the M&A deals and it is in contrast to the first research question of this study that allow the presence of breaks both prior and subsequent to the announcement day.

In order to fulfill the 15% trimming factor and minimum sample size of 100 correlations requirements the researcher can only determine *N* since *C* is a random variable and uniquely specified for each deal. On the whole, *N* is a function of *C* and it is determined as follows:

$$N = \begin{cases} 100 - (C+1) + 21 \ , & 19 \leq C \leq 29 \\ \frac{C+1}{0.3} - (C+1) + 21 \ , & 30 \leq C \leq 251 \end{cases} \qquad (4)$$

The equation (4) illustrates how the pre-announcement daily returns (*N*) of both pair-firms are collected for each deal in the sample in order to investigate the possible shifs in the return correlations. First, all M&A deals that are consummated in less than 19 days(*C* < 19) are excluded from the sample of the takeover deals due to the limit of 100 daily correlations and the trimming factor of 15% , otherwise the probability of shifts occurring after the announcement day would be trivial. Second, *N* is selected in all M&A deals with *C* between 19 and 29 days in such a way that the total daily correlation is equal to 100 observations. This *N* ensures that at least 20% and maximum 30% of total daily correlations are located after the announcement date so there is no experimental concern related to the probability of break after the reference date. Third, for all deals with *C* between 30 and 251 days (the majority of the M&A deals are in this group), *N* is determined in a way that only 30% of total daily correlations are located after the announcement date. This fixed proportion (30%) indicates that the possible post-bid break can only happen in the first half of *C* days (15% of total daily correlation after the announcement day). Finally, all takeover transactions whose consummation period lasts more than 1 year (C > 252) are excluded from the sample due to the excess noise can be added to the return series because of the delay in the delisting of corresponding target firms (this dropping is in line with the sample selection in Schwert (1996)). Overall, *N* is determined in all cases in a way that the investigator can observe only one break, if any, after the announcement date by using the BP method as the major focus in this paper is on detection of multiple breaks prior to the bid announcement.

BP (2006) find in their simulations that correcting for distributional heterogeneity in the data and (or) errors across segments and serial correlation can considerably improve the coverage ratio of confidence intervals for the structural break dates. So, Andrews's (1991) data dependent method (with the Quadratic Spectral kernel and an AR (1) approximation to select the bandwidth) is used to construct a covariance matrix robust to the heteroscedasticity and serial correlation (the HAC estimator) in the residuals of regressions (3). Moreover, the HAC standard errors are constructed by allowing the distributions of the correlations and errors to differ across segments.[13]

4.3. Empirical Models

The Probit and Poisson models are estimated in this paper to provide empirical evidence on the determinants of the likelihood of observing pre- and (or) post-announcement shifts in the mean of correlations (i.e., *Prior-Break-Dummy and After-Break-Dummy as* binary outcome dependent variables) and the number of breaks per deal (i.e., *No.Breaks* as a count outcome dependent variable), respectively.[14]

4.3.1. Determinants of Anticipation and Reaction Breaks

A set of regressors based on the acquisition, pre-deal target and acquirer characteristics is used in the Probit and Poisson regressions which are listed and explained in Table 1.

---

[13] Although BP provide the option to apply Andrews and Monahan (1992) pre-whitening prior to estimating the long run covariance matrix, this option is not considered in this paper since Sul et al (2005) provide evidence that the pre-whitening can lead to biased HAC estimates which, in turn, can reduce significantly the power of structural break tests.

[14]All the binary and count outcome dependent variables are determined after detecting shifts in the mean of correlation series of each deal via the SBM. No.Breaks is a cardinal number taking values 0, 1, 2, 3, 4 and 5.

4.3.1.1. Acquisition Characteristics

The acquisitions characteristics are mostly determined at the announcement day or afterwards. While most of the M&A studies report the Cumulative Average Abnormal Returns (CAARs) for a few trading days surrounding the announcement day, the largest returns to the target shareholders is documented at the bid announcement day (e.g., Holmen et al, 2010). So, the returns at the announcement day of bid offer were computed for both of target and acquirer shareholders.

A similar interval as Schwert (1996) is used to compute the post-bid markup (or control) premiums to the target and acquirer shareholders.[15] However, Schwert (1996) used CAARs to compute markup premiums while the buy-and-hold log returns are used in this paper.

Since Ismail et al (2010) find that firms with high (low) correlations tend to offer share (cash) as a payment form, it seems that method of payment plays a key role in describing the likelihood of break(s) in the correlations around the announcement day. So, the payment dummies are defined: whether the payment to the target shareholders was only in the form of cash (*Cash*), equity (*Equity*) or a combination of these payment forms (*Mix*).

It is expected that the horizontal mergers are more likely to be anticipated due to active monitoring by rivals or industry-specific market investors, and so a variable (*SIC* dummy) is defined to capture the industry relatedness between the target and the bidder firms.

Since a higher probability of anticipation is also expected for deals with *news*, a dummy variable for the existence of any *news* about the takeover transactions at pre-announcement period is defined.

Year-dummy variables based on the year in which the first bid was announced are used to control any unobservable effects of macroeconomic factors in the regression estimates.

4.3.1.2. Pre-deal Target and Acquirer Characteristics

The pre-deal regressors are used in this study is related to the various M&A theories and measured based on the data available at the end of the fiscal year prior to the merger announcement. Since there is a time lag between these pre-deal characteristics and the bid announcement, it seems that the pre-deal variables are exogenous.

According to the asymmetric information hypothesis acquirers with relatively overvalued shares compared to those of targets tend to offer their shares as payment form, otherwise they offer cash.[16]And since payment form is related with correlations (Ismail et al (2010)), the Tobin'Q of acquirer and target are used in the regressions to capture this effects.

It is well known that acquirers offer control premium to the target shareholders based on their own valuation about the target's business and the expected synergy from merging. Thus, the enterprise value to operating revenue multiples (measured as the sum of pre-deal market value of equity and

[15] He used return data from the day of bid announcement through delisting of target's shares or 126 trading days after the first bid, whichever comes first, to construct the interval. But data from day 0 through delisting target's shares (i.e., *No-Obs-Aft, C)* is used in this paper. The difference between these definitions in the sample is only 18 deals in which the target's stock is delisted after 126 trading days.

[16] See, for instance, Shleifer and Vishny (2003) for discussion about the impact of asymmetric information on takeover transactions.

book value of debt minus cash & cash equivalents divided by its total turnover) for both of target and acquirer firms are employed as control variables.[17]

Capital structure of the target and acquirer firms can influence the payment form and, in turn, premiums in acquisitions. It is difficult for a highly leveraged acquirer to raise sufficient debt to finance cash payments. The leverage ratio of target and acquirer, *TARG-LEV* and *ACQ-LEV*, measured as the ratio of the debt and the book value of assets at the end of the fiscal year prior to the merger announcement is also used as regressors in this paper.

The size of firms is relevant in determining the method of payment or the size of bid premium offered to the target shareholders. Thus, *ACQ-Size* and *TARG-Size* are included in the regressions. The relative size of target to acquirer firm is also added as the regressor in the Probit and Poisson models to capture any non-linearity in the size of pair-firms. Moreover, the relative size has explanatory power in the choice of payment form in mergers as the bidder needs a substantial amount of cash to acquire a large target firm (Ismail et al, 2010).

4.3.2. Modeling Strategy

The strategy in selecting regressors in this paper is akin to the general-to-specific modeling approach to avoid the danger of data mining as it is particularly high in simple to general specification approach (see Charemza and Deadman (1999) for an extensive discussion). Therefore, for each of dependent variables in this paper, a general unrestricted model (Model 1) is built on the full set of carefully aforementioned explanatory variables related to the acquirer, target and deal characteristics. Including all seemingly relevant variables in Model 1 reduces considerably the risk of omitted variable bias. Model 1 provides an overview about highly insignificant and irrelevant regressors in each regression. As discussed in econometric literature, including those irrelevant regressors will typically increase the variance of the estimators for the other model parameters and reduce accordingly their *t*-statistics and their statistical significance. [18] The Wald test is used to examine the joint insignificance of those irrelevant variables in Model 1. The second and more parsimonious model (Model 2) is thus constructed by excluding those irrelevant variables. The Schwarz (1978) Bayesian Information Criterion (BIC), the χ^2- value of joint Wald test for significance of regression coefficients and the *t*-statistics of variables in Model 2 also confirm that the nested model is more appropriate for the analysis. Hence, the main results and interpretations are based on Model 2 of each regression.

[17] The investment community frequently use the price-earnings multiple (PE) or the Enterprise Value to EBITDA multiple to assess relative valuation of firms. However, since a major proportion of firms have negative EBITDA and net income in the sample, the measures for earnings multiples (i.e., *ACQ-MV/Turnover* and *TARG-MV/Turnover*) is more relevant in this study.

[18] The comparison of *t*-statistics of Model 1 and 2 in Table 6 confirms this claim as the *t*-statistics in Model 2(the nested model) is frequently larger than of those in Model 1 (unrestricted model).

5. Data and Descriptive Statistics

5.1. Sample Selection

Martinova et al (2008) demonstrate that the beginning of the latest takeover wave (the 6th M&A wave) in mid-2003 coincides with the gradual recovery of economic and financial markets after the IT bubble recession that began in 2000.They also anticipate that the M&A activity will slow down after the recent 2007 financial crisis. So, both of financial market and market for corporate control are expected to be stable over the period of mid-2003 to mid-2006.This is the reason why the period of mid-2003 to mid-2006 is selected as the sample period in this paper. The choice of this stationary period ensures that the observed multiple shifts in the mean of unconditional correlations are not a consequence of abrupt fluctuations in the stock prices induced by the macroeconomic or industry factors. Thus, the estimated shifts around the announcement day are solely driven by the release of new information (private and (or) public news) about the takeover transaction.

When an acquirer has multiple bid records in the sample, the first bid is only considered if the interval between its consummation day and the second bid announcement date is more than six months; otherwise all bids related to this acquirer are excluded. The reason is the following. Since some observed post-announcement returns to the bidder in the earlier acquisition are indeed used in the pre-announcement returns to the same bidder in the later acquisition, the observed pre-announcement shifts in the later case can be induced by the announcement of both bids and cannot be distinguishable which one is dominant in determining the breaks. For avoiding this potential problem all multiple bids in the original sample over the period of Jan. 2003 to Dec. 2006 are first identified and dropped .Then, the main sample is extracted by excluding all offers which announced during the first half of 2003 and the second half of 2006(the isolation intervals). The identification of isolation intervals prevents any potential biases related to the acquirers with multiple bids prior to 2003 and after 2006.

To study the multiple shifts in the mean of unconditional correlations between the target and the bidder stock returns, I use the Bureau Van Dijk Zephyr database containing firms' accounting and deal information about all successfully completed acquisitions between U.S. publicly listed firms which announced between 1 July 2003 and 30 June 2006. Adjusted daily-closed prices of securities are from Thomson Financial DataStream. All financial institutions as acquirer and (or) target firms and any deals with a value less than $50 million were excluded from this sample. [19] The all-cash, all-equity and a combination of these payment forms to the target shareholders are only considered in the sample deals in which a bidder gains entire control of the target firm by acquiring 100% of the target's shares, eventually leading to delisting of the target's stock (so partial or cleanup offers are excluded). Furthermore, all deals that took longer than one year or shorter than 19 trading days to consummate and any deals in which the target's pre-announcement (roughly, two months before the announcement day) stock price is remarkably low (below 2$ per share) were dropped. [20] With these

---

[19] Since financial institutions are extremely leveraged, they are excluded from the sample to prevent any errors associated with the use of accounting measures (as regressors) in the estimation models.

[20] Schwert (1996) argues that the returns to these low-priced stocks could be imprecise as they are probably more exposed to frictions in the market microstructure.

restrictions, I identified 125 deals with enough return data available to construct daily log returns and the SMA correlations. The main sample, however, was further reduced due to the unavailability of some observations for certain explanatory variables that were included in the regressions.

5.2. Descriptive Statistics

The descriptive statistics related to the acquisitions, pre-deal target and acquirer characteristics are summarized in Table 2, providing insights into the nature of the sample data investigated in this paper. The sample is split to 54 all-cash, 33 all-equity and 38 mix-payment deals. More statistics of those characteristics based on the payment subsamples are also presented in Table 2.In 57.6% of deals in the sample the acquisition is between firms within similar industries (*SIC*=1).

For each of the 125 acquisitions, I calculated daily time series of log-returns to both of the target and acquirer shareholders. The total number of daily returns is not constant for each deal and is indeed a function of *C* (i.e., *C* determines the total sample size for each deal). The average and median for the total daily returns per deal in the sample is respectively about 302 and 270 trading days in which 83 of these returns are on average located after the announcement day. Moreover, the average number of daily returns before the first bid is 218 trading days in the sample which is somehow analogous to those event studies that use about 200 daily returns to estimate the parameters. [21]The low average consummation time (i.e., *C* is defined as the number of trading days between the announcement and delisting of target‘s stock exchange) for all-cash subsample points out that the target shareholders that receive *Cash* are delisted earlier than others payment subsamples. The large F-value of ANOVA model (11.17) implies that the average consummation time is significantly different between *Cash, Equity* and *Mix* subsamples.[22]

It is a well-known fact that the most benefits of takeovers announcements are received by target shareholders and the announcement returns to acquirers are either insignificant or slightly negative (e.g., Schwert, 1996), a result reproduced here again. The average return to the target shareholders at day 0 is significantly positive (11.9%) while this measure for acquirers is statistically negative (- 1.5%), though its magnitude is economically insignificant in the sample.[23] The mean and median tests also confirm the significance of this difference between averages. The result for subsamples in Table 2 indicates that the announcing of bid offers with cash as a payment form to the target shareholders generates a higher significant average returns to the target shareholders (21%) compared to average returns in *Mix* offers (11.3%) and *Equity* offers (7%). The ANOVA analysis also points out that average subsample announcement returns to the both of target and acquirer shareholders is statistically different, proposing that the acquirers on average offer higher bid premiums in all-cash offers and lower premiums in all-equity offers. The market reacts to this lower bid premium with undervaluation of the acquirer’s share price at announcement day (the average

---

[21] For example, Ismail et al (2010) used 210 to 20 trading days prior to the day 0 as the estimation period.

[22] The one-way Analysis-Of-Variance (ANOVA) model is particularly suitable for multiple comparison of equality-of-means hypothesis for subsamples related to a variable (see Hochberg et al (1987) for discussion about these models).

[23] This result is in line with the work by Holmen et al (2010), who find for large Swedish non-financial firms during 1985-2005 that the largest announcement returns to the target shareholders occurs at day 0 and it is about 17.9%.Ismail et al (2010) also report for mergers between publicly listed US companies from 1985 to 2004 that the Average Cumulative abnormal returns (in a time window from days -5 to +5) to the target shareholders is 16.3% and -4.2% for acquirers.

returns is -3.3%) since they might interpret that acquirers usually offer equity when their share price are overvalued.

The average markup premium to the target shareholders in the sample is significant and equals to 20% and this figure for the acquirer is slightly positive (2.7%) but statistically insignificant. The mean and median tests also show that the difference between averages is significant. This result is comparable to Schwert (1996)'s findings in which target's markup premium for successful tender offers is 20.1% and insignificant for the acquirers (2.5%).

There are only 21 deals in the sample with rumors (*news*) prior to the first bid offer. When the sample is split into rumored and non-rumored deals, the difference between averages announcement returns for these subsamples are significant at conventional levels. Similar results are obtained for the markup premiums.[24]

The median acquisition in the sample has a deal value of 428.16 million U.S. dollars. The average deal value for all-equity subsample ($ 5339.72 million) is much larger than all-cash subsample ($ 469.45 million) suggesting that the size of target is significant in the choice of payment form. The mean and median tests in Table 2 suggest that the acquirer has more assets than the target firms, however, according to ANOVA model; target's larger asset is on average associated with Equity offers. The ANOVA analysis indicates that the average relative sizes among payment subsamples is statistically different. Table 2 shows that the fraction of acquirer's shares used by bidders to finance the acquisition increased on average by the relative size of target to acquirer firm. The payment form to the target shareholders is on average *Equity* when the target is about the same size as the bidder.

5.3. Modeling Daily SMA Correlations and Related Averages

I computed daily rolling SMA correlation series for each of 125 deals in the sample. The mean and median for *No-Corr* is 279.7 and 248 daily rolling correlations in the data set, respectively (more related statistics is reported in Table 2).

The average daily SMA correlation at day t is computed as the average of all SMA correlations at that day. The main sample is used to calculate the averages between day -72 and day 28 (relative to announcement, day 0), however, departing further from this interval reduces the sample size day to day. The sample is thus restricted to a period from day -117 to day 47 (166 daily observations) as at least 100 (out of 125) deals are used to construct the average daily correlations. So, the most of observed fluctuations in average daily correlations can be related to the bid offer in this period.

The average daily SMA correlation series for the main sample and subsamples (i.e., All-Cash, All-Equity and Mixed-Payment subsamples) between day -117 and 47 are depicted in Panel A of Figure 2 to provide insights about the general pattern of correlations around the announcement day. There are two obvious results from this graph. First, the average daily correlation for All-Cash subsample is considerably lower than the All-Equity and Mixed-Payment subsamples throughout the sample

[24] This result is consistent with the work by Schwert (1996), who finds that the deals with news have higher average returns to the target shareholders around the announcement day. Contrary to the result, he demonstrates lower average markup premiums for acquirer shareholders in deals with *news*.

period. The unreported mean *t*-tests also confirm that the differences between observed average daily correlations among subsamples are significant. This fact suggests that the acquiring firms on average tend to offer cash payment to the target shareholders when their returns are weakly correlated and to offer their equity as a part of (or entire) payment when their returns is highly correlated at the pre-announcement period. This evidence is consistent with the work by Ismail et al (2010). [25] Second, Panel A of Figure 2 shows that the announcement of bid offers, regardless of the method of payment, coincides with a sharp fall in the average daily correlations which is contrary to the expectation that announcing a merging (i.e., stock swap transaction) offer should raise on average the correlations. Although the average daily correlations remain in a low level or change slightly after day 0, they jump to the high level (except cash deals) at day 22. This odd post-announcement behavior of average correlation can be related to the influential effect of the returns at the announcement (day 0) as the time lag between abrupt rise and fall in average daily correlations is exactly 21trading days which is the size of rolling window used by the SMA method. The following section will discuss more about the high probability that the announcement returns to the target and acquirer shareholders are outliers in the sample daily log-returns.

5.4. The Influential Effect of Announcement Returns as Outliers

The univariate statistical outlier detection method introduced by Ben-Gal (2005) is applied to each of 125 deals in the sample to detect all outliers in the sample distribution of daily log-returns to the target and acquiring stocks. [26] The outlier detection analysis shows that the announcement return is an outlier for 72 target and 24 acquiring firms in which these returns are the largest outlier for 46 target and 11 acquiring firms. So, the announcement returns to the target and (or) acquiring firms are outlying in a large fraction of deals in the sample. This suggests the potential effect of these outliers in generating biased estimate of daily SMA correlations and the related break estimates.

Panel B of Figure 2 illustrates that exclusion of announcement returns as outlier affect dramatically the post-announcement correlation series, as expected. It is evident from this figure that there is a positive relation between the fraction of shares offered by the acquirer and the increase in the post-announcement average daily SMA correlations. On the other hand, announcing cash offers lead on average that the returns to the pair-firms to become uncorrelated.

Table 3 demonstrates that there are two break dates in the mean of average daily SMA correlations at day -57 and day 22 for the sample when the announcement returns are excluded. There is at least one break at pre-announcement period regardless of payment form which confirms the expectation that the market can anticipate the bid offer in M&A deals. Moreover, the market correctly reacts to the

[25] However, they use point estimates of correlation as a regressor in the Tobit regressions to explain the positive relation between the return correlations and the fraction of shares paid by acquirers while the similar result are simply obtained by modeling the dynamic feature of correlations over time.

[26] According to Ben-Gal (2005) , an observation is considered as an outlier if its absolute deviation from the median of sample divided by the standard deviation of sample is larger than 1.96 (corresponding to Z-value of the 5% significance level in normal distribution). The medians for all daily log-returns are assumed to be zero (which is almost consistent with the sample) and they are normally distributed. A stricter rule is imposed for detecting a daily log-return as an outlier: the Z-value is increased to 3 (corresponding to the 0.27% significance level) to reduce the probability of incorrectly accepting a daily log-return as an outlier.

announcement of bid offers based on the offered payment form to the target shareholders. The mean of average correlations shifts towards perfect correlation in *All-Equity* or *Mixed*-payment offers and remain in lower levels without any structural change in *All-Cash* offers. The comparison of these results with the unreported case where the announcement returns are not excluded reveals the influential effect of announcement returns as outliers in changing the results of Structural Break analysis.

The conclusion is that the announcements returns to the target and acquirers are outliers in the sample. Therefore, these returns are excluded from the sample log-returns of each deal before they can result in biased daily SMA correlations and any spurious structural break outputs for the mean of correlations. However, the effect of excluding these announcement returns on the estimated break dates and the parameters of the Probit and Poisson regressions will be discussed in detail in the robustness section.

The breaks in the average daily SMA correlations presented here might not be identical to the average of break dates in daily SMA correlations per deal due to the variation in the size of sample correlations among deals. Moreover, averaging of all SMA correlations per day in the former case can wipe out most of the specific information related to each deal and its participants. Thus, the conclusions should be extracted from the results of performing SB analysis for each of 125 deals in the sample which is documented in the next section.

6. Results

I performed structural break analysis for each of 125 acquisitions in the sample. [27] Table 4 summarizes the number of multiple shifts in the mean of daily SMA correlations of each deal in the sample and the general location of these break dates relative to the takeover announcement (day 0). The SB results are summarized and tabulated in Table 5. Moreover, the estimating results of Probit and Poisson regressions are reported in Table 6. While the average marginal effects are reported in Table 6, for convenience, the average elasticities are interpreted for continuous regressors throughout the text in this paper.

A total number of 320 break dates are detected in the sample. Figure 3 illustrates the frequency distribution and the box plot of these break dates relative to the announcement (day 0). The histogram shows that most of the 320 breaks are located around the announcement and the box plot at the bottom of this histogram demonstrates that more than 70% of them are located prior the announcement day.[28]

Although detection of multiple shifts conveys relevant information about the non-stationarity feature of unconditional correlations over time, the reason for observing those breaks are unknown for the researcher if they are located too distant from the announcement day. This is the reason why the main focus is particularly on the 1st pre-announcement break and the proposed approach is limited to

---

[27] I would like to thank Jushan Bai and Pierre Perron for providing the GAUSS code of the Multiple Structural Break Methodology. The Version 4 (February 24, 2009) of this code has been used in this paper.

[28] The box plot shows that the inter-quartile (3rd quartile – 1st quartile) range from day -81 to day 9 and the median and mean equal to day -34 and day -45.6, respectively.

identify only one break after the announcement day in this paper. Observing 63% of total break dates (320 deals) around the announcement day confirms that these two breaks are closely associated with the bid announcement, and so their interpretability as the market anticipation and reaction is more understandable. Therefore, the size and sign of shifts in the mean of daily correlations in the regimes after the first pre- and the post-announcement breaks are crucial in investigating how accurate the market anticipates and reacts to the announcement of bid offers, respectively. If the market accurately anticipates and reacts to the payment form in pre- and post-announcement periods, the average correlation should increase for *Equity* and *Mix* deals and decrease for *Cash* deals.

6.1. Anticipation of Bid Offers

Observing at least one pre-announcement break in 84% of deals in the sample leads to conclude that the market can effectively anticipate the bid offers (see Table 4). This finding is an obvious evidence of the main inspiration that the multiple shifts in the mean of dynamic unconditional correlations can anticipate the pair-firms in the takeover transactions.

The existence of 25 out of 125 deals with breaks only at the pre-announcement period in Table 4 implies that the market anticipation is more dominant than the post-announcement reaction. The 1st pre-announcement break in these deals shifts the mean of correlations towards the target level, and so the market surprisingly anticipates entirely the deal, the payment form and the bidder who will successfully acquire the target at the post-announcement period.[29]

6.1.1. Pre-Announcement Break Dates

Panel B of Figure 3 and Table 5 show that the median and mean anticipation date (i.e., *1st-Break-Prior)* is 27 and 54.4 trading days prior to the announcement (day 0) in the total sample, respectively.[30]

A close similarity between the average 1st pre-announcement break date at day -54.4 and the pre-announcement break date of average daily correlations at day -57 has two important implications: First, the convergence of these two dates to each other lead to conclude that the effect of bid announcement in correlation series is too big to disappear by averaging of all correlations per day. Second, the choice of only the first pre-announcement break among others and interpreting it as the anticipation date of bid offer is completely relevant as only one similar break date exists in the average daily correlations. Therefore, the market anticipates the bid offer on average 54 trading day prior to the announcement day.

Panel B of Figure 3 illustrates that the larger the fraction of acquirer's shares paid to the target shareholders, the earlier the anticipation date is. Moreover, the ANOVA model in Table 5 points out that the average anticipation date is statistically different from zero (at the 5% level) between the *Cash, Equity* and *Mix* subsamples. *Equity* deals are on average anticipated much earlier than other

[29] The target level is perfect or strong correlations in *Equity* and *Mix*-payment deals and weak or non- correlations in *Cash* deals.

[30] The skewness in the distribution of anticipation breaks suggests the effect of some influential break dates. However, the 90% of the total 1st pre-announcement break dates are observed in an approximately semi-annual interval from the announcement day (between day -139 and day -1).

payment subsamples (i.e., day -81 for *Equity subsample* compared to almost day -45 for the others). This evidence might be interpreted as the ability of markets not only to anticipate the takeover offers but also the payment form. However, this early anticipation in *Equity* subsample can be partially explained by its larger average sample correlations size compared to the other payment subsamples (see the *No.Corr* statistics in Table 3). When the total number of correlations in a sample deal is large, the SBM impose more observations between subsequent break dates due to the fixed trimming factor. This argument reveals that the result of the univariate ANOVA analyses is inconclusive and the related shifts in the correlations are needed to be investigated to draw valid conclusions about early anticipation of *Equity* subsample.[31]

6.1.2. Pre-announcement Shift in the Correlations: Equity vs. Cash Offers

The mean of correlations increases for *Equity* and *Mix* subsamples (0.142 and 0.109, respectively) more than *Cash* deals (0.039) after the 1st pre-announcement break. However, the result of ANOVA model in Table 5 indicates that the observed differences in the average shifts across payment subsamples are statistically insignificant. If the market anticipated truly the payment form, one could observe on average a downward shift in the mean of correlations for *Cash* deals and the highest upward shift for *Equity* offers after the anticipation break. This is not the case in this study. Thus, the market is entirely incapable to anticipate the payment form via the pre-announcement shifts in the mean of correlations.

6.1.3. Predicting Bid Offers

The nested model (Model 2) in panel A of Table 6 shows that the average probability of observing a pre-announcement break increases by 14.13% (t-statistic of 2.27) if the target and acquirer firms are from same industry (*SIC*=1). The statistical and economical significance of *SIC* indicate that horizontal M&As are more likely to be anticipated by the market compared to the diversifying takeovers. This can be explained by the fact that the acquisitions are more likely to occur between firms in the same industry due to a higher synergy effect for merging firms.[32] The market therefore monitors actively firms in the same industry and predict possible M&As among them.

The next-best predictor after the *SIC* is the target's Tobin Q. A 1% increase in the average probability of having a pre-announcement break requires an increase in target 's Tobin Q of 9.3 %(t-statistic of 1.87). This positive relation shows that the bid offer is more likely to be anticipated if the target has more intangible assets and (or) growth opportunities. The same effect requires a decrease of 11.1% (t-statistic of -2.03) in the relative size of target and acquirer (*REL-Size).*This means that when the target is much smaller than the acquirer in terms of market value, it is more likely to

---

[31] The inability of univariate analyses motivates to use the multivariate OLS regression to examine the determinants of pre-and post-announcement break dates. However, several serious problems will arise when one attempt to estimate these OLS regressions. The major problems are the simultanity bias between the pre- and post-announcement break date equations, the endogeneity of consummation time (i.e., C) and the selection bias. The insignificance of Inverse Mills Ratios in Heckman's (1979) two-step models indicate that there is no selection bias and the Probit (selection equation) and the OLS models can be estimated independently. However, the lack of proper instrument variables that only correlated with one of these two break dates leads to leave the estimating the determinants of pre-and post-announcement break dates for further research.

[32] This is also evident in the sample as the major fraction (58%) of total acquisitions is between pair-firms from a similar industry.

observe an anticipation shift in their correlations.[33] The coefficient estimate for the total assets of acquirer (*Ln (ACQ-Size))* is slightly significant (t-statistic of 1.73) as its increase by 20.3% can only raise the average probability of anticipation by 1%. The combination of size with relative size variables captures any non-linearity in the relation between the size of target and acquirer and the likelihood of anticipation. For instance, suppose that the relative size in two deals are equal in the sample, the one with a larger acquirer‘s total assets is more likely to be anticipated compared to the other one.

Among the predictors of the anticipation regression, insignificance of *News* is odd as a positive relation is expected between rumor about the deal and the likelihood of observing pre-announcement breaks.[34] It is positive but statistically insignificant in the anticipation regression which suggests that the market does not rely on the *News* in anticipating of a deal. Moreover, the irrelevance of *No-Corr* and payment dummies show that the sample size and the payment forms cannot predicts the bid offers.

6.2. Reaction to Bid Announcements

Table 4 shows that the post-announcement breaks are observed in 96 out of 125 acquisitions (76.8% of deals) which suggest that the market reacts to the public bid announcements. Moreover, if these shifts are upward in *Equity* and *Mix*-payment subsamples and downward in *Cash* deals, one can conclude that the market further anticipates the delisting of target’s stock due to the successful acquisition. This line of interpretability associated with the post-announcement breaks also implies the efficiency of the proposed approach in extending the rolling correlations to the post-announcement period.

When the number of breaks per deal is more than one (95 deals) in Table 4, the breaks split more around the announcement day (80 out of the 95 deals) rather than to concentrate in the pre-announcement period (15 out of the 95 deals). This proposes that the market reacts actively to public bid offers. This split indicates the remarkable effect of the bid announcements in shifting the joint distribution of returns around the announcement day.

6.2.1. Post-Announcement Break Dates

Panel C of Figure 3 and Table 5 shows that the median and mean reaction date (i.e., *Break-After)* in the total sample is 19 and 18.73 trading days after the announcement (day 0), respectively. These statistics indicate that the distribution of total reaction dates is centered on day19. The nearness of the average of post-announcement break dates at day 19 to the post-announcement break in the

[33] Targets are often smaller than acquirers in terms of pre-deal market value. This is also the case in the sample since the target is smaller than the bidder in 88% of all available data for the relative size.

[34] The announcement returns and markup premiums for both firms are not included in the unrestricted Probit models for *Prior-Break-Dummy* in panel A for two reasons. First, the entire model becomes insignificant at any conventional level when they are included. Second, these variables are mainly determined at announcement day and afterwards so using them as predictors might by invalid for the break at the pre-announcement period.

average daily correlations at day 22 indicates that the market reacts on average to the announcement of bid offer at day 19.

6.2.2. Post-announcement Shift in the Correlations: Equity vs. Cash Offers

Table 5 demonstrates that the size of average shift in the mean of correlations after the post-announcement break (0.269) is larger than that of the pre-announcement break (0.089), which is also confirmed by the unreported mean *t*-test at the 1% level. This significant difference indicates that the market more confidently shift the mean of correlations at the post-announcement period as the bidders' aim to acquire the target firm has been already announced.

Table 5 shows that, as expected, the announcing of bid offer boosts (i.e., *Change-Mean-Corr-Aft*) considerably and on average the mean of correlations in *Equity* and *Mix*-payment deals (0.469 and 0.433, respectively) after the post-announcement break while the mean of correlations for *Cash* deals falls on average (-0.059). The ANOVA model also figures out that the observed differences between these average shifts across payment subsamples are highly significant at the 1% level. Its large F-value (34.09) implies that the market reacts significantly to the public announcements and shift the mean of correlations towards the target level based on the offered payment form by acquirers (i.e., towards perfect correlations in *Equity* and *Mix*-payment deals and non-correlations in *Cash* deals). Therefore, that the market not only reacts to the bid announcements but also increases the likelihood that the bidder firms will successfully acquire the target firms.

6.2.3. Predicting Reaction to Bid Announcements

The nested model in Panel B of Table 6 shows that the most economically significant predictor of the likelihood of reaction to the public announcements is the *Cash* payment. Offering all payment in *Cash* reduces the average probability of having a post-announcement break by 13.4% (t-statistic of -1.65) compared to the *Equity* or the *Mix*-payment offers. As shown in the average daily correlation case when the returns to the pair-firms are weakly correlated at the pre-announcement period the acquirers tend on average to make *Cash* offers. Thus, announcing a cash offer cannot shift weak correlations as they are already at the post-announcements target level for cash deals (i.e., non-correlation).

Like the result of Probit regression for the anticipation break, a 1% increase in the average probability of having a post-announcement break requires an increase in target 's Tobin Q of 9.7 %(t-statistic of 1.89). This similarity suggests that the market is more likely to anticipate and to react to the bid announcements in which the targets have higher Q (ceteris paribus). This means that the market realizes that these targets are more likely subject to the bid offers that will be consequently consummated successfully. The same effect requires a decrease of 16.2% (t-statistic of -2.35) in the target's valuation multiple (*TARG-MV/Turnover*). If the target is overvalued relative to its operating revenue, the market is less likely to anticipate the successful acquisition of the target. Moreover, the market is less likely to react to the bid announcement if the returns to the acquirer are positive at the post-announcement period (*ACQ-Mark-up*) as its Probit estimate is significantly negative (t-statistic of -2.13). So, the market is less likely to anticipate that the offer will be successfully consummated if the acquirer gains on average at post-announcement period. This is understandable if it is assumed that the post-bid markup premium to the acquirer shareholders is on average insignificant or slightly negative.

6.3. Number of Breaks per Deal

Observing at least one break in 96.8% of the sample deals in Table 4 implies that the daily SMA correlations are indeed time-varying in the takeover transactions. So, those methods (e.g., the event study method and the Multivariate GARCH class of models) which are based on the unconditional covariance stationary assumption can generate biased results.[35]

The existence of 4 deals without any breaks (and 26 deals with only one break) can be empirically interpreted as the reliability of SBM in estimating a reasonable number of breaks (against the spurious number of breaks) in the unconditional rolling SMA correlations.[36]

The empirical strategy limits the number of breaks up to 5 breaks per deal while at most one of them can be located after the announcement day. This strategy describes why all breaks are split around the announcement day when the SBM detect 5 breaks per deal. Meanwhile, observing only 6 out of 125 deals with 5 breaks in each of them indicates that the choice of this maximum number of breaks per deal is relevant for this study.

6.3.1. Predicting Number of Breaks per Deal

Panel C of Table 6 shows that among deal characteristics, only acquisition between firms in a similar industry (*SIC*=1) is both statistically and economically significant in explaining the number of breaks per deal. The average number of breaks per deal increases by 63.19% (t-statistic of 2.27) if the target and acquirer firms are from same industry (*SIC*=1). Since the horizontal M&As are more likely compared to diversifying acquisitions, the market monitors actively potential takeover transactions between firms in the same industry. Moreover, the results in the previous section shows that the likelihood of observing breaks around the announcement is on average higher when pair-firms are in the same industry. Thus, on average more breaks in correlations per deal for horizontal M&As are observed compared to diversifying acquisitions.

The relative size of target and acquirer (*REL-Size)* is the next-best predictor of the number of breaks per deal. A 1% increase in the average number of breaks per deal requires a decrease in relative size of target and acquirer of 18.5 %(t-statistic of -2.76). This implies simply that when the market value of target differs significantly from that of acquirer, the market is more likely to anticipate the deal and impose more shifts in their return correlations around the announcement of bid offer. This

---

[35] This line of interpretation about the potential discrepancy of event study methodology is also reported by Burnett et al (1995). They investigate non-stationarity in the market model parameters and find that only 10% of firms in their sample generate neither breaks in-the-sample period nor in the event window. However, they use less compatible method(i.e., the switching regression methodology) compared to the SBM applied in this paper to investigate structural changes in event study for a sample of 95 stock split announcements in U.S. from 1978 to 1989.

[36] Since the returns to those 4 Cash deals are uncorrelated at the pre-announcement period, their bid announcements do not change substantially the level of correlations in the post-announcement period. This is the reason why the SBM cannot detect any breaks in these 4 deals.

negative impact of relative size on predicting the number of breaks per deal can be offset by the positive effect of acquirer's size (*Ln (ACQ-Size))*. The same effect requires an increase of 18.6 % (t-statistic of -2.76) in the total assets of acquirer. The combination of these two predictors captures nonlinearity in the size effect on the predicted number of breaks per deal, as in the anticipation regression (Panel A of table 6). For instance, if the relative size of targets and acquirers are identical for two acquisitions, the average number of breaks is higher for the deal that the acquirer has larger total assets. Although the valuation multiple of target (*TARG-MV/Turnover)* is slightly significant (t-statistic of 1.88) in predicting the number of breaks, its positive effect (i.e., average marginal effect of 0.0139) is trivial to judge to be economically significant.

The insignificance of year dummy variables in predicting the number of breaks in unrestricted model (Model 1 in panel C) confirms the objective selection of the sample period from 2003 to 2006.This stationary period is chosen in such a way that imposes a lower chance for observing spurious multiple shifts in the mean of correlations due to abrupt fluctuations in the stock prices induced by the macroeconomic or industry factors.[37]

Although the *Cash* variable has explanatory power for the likely location of breaks around the announcement day, the payment predictors are totally irrelevant in predicting the number of breaks per deal in the Poisson regression. This finding is consistent with the univariate result of ANOVA model presented in Table 5. Another statistically significant (t-statistic of - 2.46) predictor in this regression is the total number of daily correlations (*No-Corr*). However, its average marginal effect (-0.0022) is economically insignificant cause to conclude that the SBM has not imposed any spurious breaks based on the sample size.

7. Robustness Tests

Some robustness tests are provided in this section. The diagnostic tests related to the Probit and the Poisson regressions are reported in the bottom of Table 6. The comparison of Structural Break statistics between the two alternative approaches in modeling daily SMA correlations (i.e., inclusion or exclusion of announcement returns as outliers in the SMA rolls) is summarized in Table 7.

7.1. Regression Diagnostics

In practice, any econometric model may deviate from the classical assumptions of the estimation method. The aim of this section is to check the validity of the main assumptions required when the Probit and the Poisson models are used to estimate parameters.

---

[37] In fact, the daily log-returns of 14 out of 27 deal announced during the second half of 2003 are started during the IT bubble (here, the first half of 2002). So, if the market fluctuations during the crisis period can generate spurious breaks in the correlation series, there should be a positive relation between the 2003 dummy and the number of breaks detected via SBM which is not the case in this sample. However, an investigation for the effect of crisis in the observed pattern of SBs in the correlations is out of the scope of this paper and left for further research.

By using the binary choice or multi-response models there is no concern related to the stochastic specification (exact distribution) of residuals but by construction, these models suffer from Heteroskedasticity problem. Henceforth, in all estimated regressions the so-called Heteroskedasticity and Autocorrelation consistent (HAC) standard errors are used to robustify the test statistics.

In building the Probit and Poisson models, first, the link function of the outcome variable on the left hand side of the equation is assumed to be the correct function(i.e., the Normal and Poisson function in the Probit and Poisson regression, respectively) to use. Second, it is assumed that all the relevant variables are included on the right hand side of the equation and the abovementioned functions are linear combination of the predictors. Violation of these two assumptions leads structural specification error which makes all the results inconsistent and/or biased, since maximization of the likelihood function is based on this functional form assumption.

As discussed in the modeling strategy section, the general-to-specific modeling approach is utilized to minimize the risk of omitted variable bias and to select the most relevant regressors in the nested model (Model 2) of each regression. However, Link test (developed by Pregibon (1979)) is used to test that all the relevant explanatory variables are included in the estimated model (i.e., no omitted variable bias) and the link function of the outcome variable is a linear combination of the regressors. According to the result of link test performed for each model and presented in Table 6, there is no concern related to the omitted variable bias and link misspecification at any conventional level.

Furthermore, Hosmer-Lemeshow test is applied to test any deviation from the normal distributional assumption of Probit likelihood function (Hosmer Jr. and Lemeshow (2000)) as non-normality will cause inconsistent maximum likelihood estimators. This test presents the χ^2 goodness-of-fit test for the fitted model and it is a test of the observed against expected number of responses. Moreover, a similar type of test is also used to examine any deviation from Poisson distributional assumption via Pearson χ^2 goodness-of-fit test. Rejection of this test means that the Poisson model is inappropriate and it is better to use a negative binomial model. However, the results of these tests in Table 6 reveals that there is no deviation from distributional assumptions, and so all the Probit and Poisson models fit the data reasonably well.

One of the structural specifications test should be done is to check for perfect linear relationship among the predictors (multicollinarity problem) which leads to unreliable regression estimates. The Variance Inflation Factor (VIF) is used to identify highly correlated regressors in the unrestricted model (Model 1) of each dependent variable. Those regressors are consequently excluded from the final parsimonious model (Model 2). The considerable reductions of Mean VIF (i.e., the average variance inflation factor of all explanatory variables in the regression) in the nested models in Table 6 indicate that the estimated coefficients are free from multicollinarity problem. [38]

The results of these diagnostic tests together with the general-to-specific modeling approach in selecting the most relevant regressors lead to conclude that the Probit and Poisson models are properly specified and their estimate are reliable for drawing conclusions.

[38] See Chatterjee and Hadi (2006) for more discussion about VIF.

7.2. How the Announcement Returns Affect the Estimates of Multiple Shifts?

The announcement returns to pair-firms are excluded from the log-return samples and the related SMA rolls (*Without* announcement return case) to avoid any potential biased results in this paper. The goal of this section is to answer the question that how the estimates of multiple shifts in the correlation and the estimates of the Probit and Poisson regressions can be affected if the announcement returns are included in the analysis (*With* announcement return case).

I estimated again the SMA correlations and the multiple shifts for each deal in the sample by including the announcement returns in the corresponding SMA rolls (*With* announcement return case). The descriptive statistics for the estimates of multiple shifts in the daily SMA correlations based on these two different approaches are presented in Panel A (*Without* case) and Panel B (*With* case) of Table 7 to make comparison more convenient.

The total number of breaks is larger when the announcement returns are included compared to excluding of them (327 vs. 320 breaks).Although this overestimation indicates the outlying effect of announcement returns, the mean and median tests in Table 7 reveals that the difference between these two cases in estimating *No-Breaks* is not statistically significant at any conventional level. Conversely, estimating the multivariate Poisson regression (i.e., the nested model in panel C of Table 6) by the estimates of *with* case result in two major differences compared to estimated coefficients of the *without* case. First, the average marginal effect of being in the same industry (*SIC*) is dropped from 63% (in *without* case) to 46% (in *with* case). Second, the relative size of target and acquirer (*REL-Size)* becomes insignificant in *with* case. Therefore, the predictors of number of breaks per deal in the Poisson regression are affected significantly by including the announcement returns.

Table 7 illustrates that the fraction of total estimated breaks located at the post-announcement period (i.e., *After-Break-Dummy*) is larger for *with* case (0.8) compared to the *without* case (0.768), but the opposite is the case for the fraction of breaks at pre-announcement period (i.e., *Prior-Break-Dummy*). However, the proportion tests indicate that the skewness in the location of breaks around the announcement is highly insignificant. The experience in the Poisson regression reveals that it is not reasonable to rely on the insignificance of those difference statistics and the entire distribution of dependent variables is need to be considered to identify the effects of announcement returns.

Except for the year dummy variable (i.e., *2004)*, neither of the anticipating predictors (see the nested model of panel A of Table 6) is significant in the Probit regression when the estimates of *with* case is used. The effect of announcement returns in changing most of the relevant predictors to insignificant ones is further continued in the Probit regressions of the *After-Break-Dummy*.[39] On the whole, the announcement returns is highly influencing the estimates of Probit regressions which confirms validity of excluding them from the SMA rolls.[40]

---

[39] The variables remained significant when the estimates of *with* case used in the Probit Regressions are *Cash* dummy in the nested model of *After-Break-Dummy* and *Cash, SIC.*

[40] This influential effect of announcement returns is also reproduced for the unrestricted models of Probit and Poisson regressions in Table 6 which reject the possibility of finding different set of predictors for the nested models that use estimates of *with* case as dependent variables.

The median at day 21 for the post-announcement break date (i.e., *Break-After)* in *with* case raises doubt about the validity of these break estimates by using announcement returns.[41] The number of deals with breaks at day 0 and day 21 in *with* case are 11 and 42, respectively. However, only 6 of these deals can retain their break dates in *without* case which shows how the announcement returns bias the estimates of break dates. Both of pre-and post-announcement break dates are anticipated late relative to day 0 in *with* case compared to *without* case (e.g., median of *1st-Break-Prior* is -24.5 in *with* case compared to -27 in *without* case). In fact, the significance of sign-rank test (Wilcoxon 1945) at 5% level verifies that including announcement returns in the SMA rolls shifts imperfectly the distribution of pre- and post-announcement break dates relative to the announcement day.

The median size of shifts at post-announcement period (i.e., *Change-Mean-Corr-Aft*) in *with* case (0.417) is significantly larger than *without* case (0.313). This suggests overestimation of the post-announcement shifts in the mean of correlations due to the outlying influence of announcement returns. Furthermore, the mean and median difference tests (t-statistics of 2.7 and z-statistics of 2.19, respectively) indicate that the pre-announcement shifts in the mean of correlations in *with* case is significantly smaller than *without* case. This is also observed in the average daily correlations sample as including the announcement returns (see panel A of Figure 2) fall sharply the mean of correlations after the 1st pre-announcement break. Therefore, the outlying effect of announcement returns is evident in dropping and raising abruptly the magnitudes of shifts at pre- and post-announcement periods, respectively.

The influential effect of announcement returns in biasing the timing and size of multiple shifts in the mean of correlations and changing dramatically the significance of predictors in the Probit and Poisson regressions lead to conclude that these returns are outliers. Therefore, the exclusion approach in controlling the outlying effects of announcement returns is appropriate in this sample, and so the above presented results are valid to draw conclusions.

8. Conclusion and Suggestions for Further Research

8.1. Summary and Conclusions

This paper provides a new solution for the bidder unpredictability dilemma in the takeover transactions. The preponderance of evidence in this paper supports the anticipation of pair-firm and the reaction to the bid announcements in takeover transactions by the market. The sample encompasses 125 successful acquisitions between non-financial exchange-listed U.S. companies from 2003 to 2006. It is explored how the existence of pre- and post-announcement breaks in the mean of correlations between the target and the acquirer stock returns can be interpreted as the market anticipation and reaction to the public bid announcement. Furthermore, the empirical evidence on the predictors of the likelihood of observing the anticipation and the reaction breaks are provided by using the Probit model. The empirical determinants of the number of breaks per deal are also documented via the Poisson regression.

---

[41] The day 21 is the first day in the SMA series without the announcement returns in its roll, so a break at this day means a sharp change in the correlation series due to the influential effect of announcement returns.

The daily rolling correlations are modeled by the Simple Moving Average method (with a rolling window of 21-trading-day). The multiple shifts in the mean of correlations for each deal are detected by the Structural Breaks Methodology (SBM). The acquirer, target and deal characteristics are used as predictors in the regressions. Some robustness tests confirm the well-specification of the regression models. However, these tests also provide evidence on the outlying effect of the announcement returns to pair-firms. Thus, these returns are excluded from the SMA rolls in order to avoid influencing the results in this paper.

The major findings based on the existence, timing and size of multiple shifts can be summarized as following:

First, in contrast to unconditional covariance stationary assumption of the event study method and the Multivariate GARCH-class of models, the unconditional daily SMA correlations are empirically documented to be time-varying in the takeover transactions. In fact, at least one break in the mean of correlations exists in 96.8% of the sample.

Second, the existence of multiple pre-announcement break(s) in 84% of the sample leads to conclude that the market can effectively anticipate the pair-firm in the takeover transaction. The median and mean anticipation date is 27 and 54.4 trading days prior to the announcement (day 0) in the sample, respectively.

Third, there is no evidence that the market is able to anticipate the payment form at the pre-announcement period.

Finally, the market not only reacts to the public bid announcements but also increases the likelihood that the bidders will successfully acquire the target firms via imposing post-announcement breaks in 77% of the sample. The median and mean reaction date at day 19 indicates that the market reacts to the public bid announcements.

The above presented results are replicated by using the average daily SMA correlation series. This similarity implies that the effect of bid announcement in shifting correlation series is too big to disappear by averaging all SMA correlations per day. Moreover, observing similar break dates for both cases around the announcement day indicates that the interpreting of the 1st pre-announcement break as the anticipation of bid offer and the post-announcement break as the reaction to bid announcement are completely relevant in this paper.

The Probit regressions show that the average probability of observing the pre-announcement anticipation break increases with being in the same industry (*SIC*), higher the target‘s Tobin Q, smaller the relative size of target to acquirer and larger the total assets of acquirer. The average probability for the post-announcement reaction break decreases with offering *Cash* to the target shareholders, lower the target‘s Tobin Q, higher the target’s valuation multiple, larger the acquirer’s markup premium.

According to the Poisson regression, the number of breaks per deal raises with being in the same industry (*SIC*), the total assets of acquirer and the target’s valuation multiple and falls with the relative size of target to acquirer.

Among those predictors, the *SIC* and *Cash* are the most economically significant regressors in predicting the bid offers (and the number of breaks per deal) and the reaction to the bid announcements, respectively.

8.2. Suggestions for Further Research

The results obtained in this paper propose several questions for future research:

First, Schwert (1996) demonstrates that the gains to the target shareholders disappear in the unsuccessful takeover transactions. This fact motivates to extend the research question of this paper to withdrawal offers to investigate whether the shifts in the correlations can also anticipate the unsuccessful offers. All M&A deals occurred during the recent crisis and the control transactions between publicly-listed financial institutions are also other possible extensions to the scope of this paper which provide further opportunities for comparison with the results obtained here.

Second, it might be of interest to investigate the determinants of the timing and size of multiple shifts in the mean of correlations around the announcement day. However, several problems are raised when one attempts to estimate the corresponding OLS regressions in this paper, the simultanity bias between the pre- and post-announcement break dates and the endogeneity of consummation time (i.e., C), which lead to leave this research question for further research. If the determinants of consummation time are specified, they can be used to estimate the simultaneous equations.

Third, the event study methodology is frequently used in the empirical finance which is based on the covariance stationary assumption. However, the existence of multiple breaks in the mean of return correlations in this paper indicates that the second-order moments are indeed time-varying. The idea is to apply the SBM to reassess the validity of earlier empirical studies (e.g., abnormal returns to shareholders in M&A deals) that are based on the standard event study methodology.

Finally, the breaks in the mean of unconditional SMA correlations in this paper suggests a potential bias in the estimates of conditional correlation models (e.g., the multivariate GARCH-class of models) since they are built on the fragile assumption that the unconditional covariances are stationary. Although the earlier studies (e.g., *Stărică* & Granger (2005)) showed that the ignored breaks in the unconditional variances lead to upward bias(towards long memory in volatilities) in the estimates of conditional GARCH (1, 1) model, such an investigations has not been conducted for the breaks in the unconditional correlations yet. The consequences of non-stationarity in unconditional covariances in estimating the multi-variate GARCH models can be another research issue to explore in further studies.

References

- Andersen, T.G., T. Bollerslev, F.X. Diebold and H. Ebens , 2001. “The Distribution of Stock Return Volatility,” Journal of Financial Economics, 61, 43-76.
- Andersen TG, Bollerslev T, Christoffersen P, Diebold F., 2006. ”Volatility forecasting”, In Handbook of Economic Forecasting, Elliott G, Granger C, Timmermann A (eds). North-Holland: Amsterdam; 777–878.
- Andrews, D.W.K., 1991. “Heteroscedasticity and autocorrelation consistent covariance matrix estimation”, Econometrica 59: 817–858.
- Andrews, D.W.K., Monahan, J.C., 1992. ”An improved heteroscedasticity and autocorrelation consistent covariance matrix estimator”, Econometrica 60: 953–966.
- Bai, J., Perron, P., 1998. “Estimating and testing linear models with multiple structural change”, Econometrica 66, 47-78.
- Bai, J., Perron, P., 2003a. “Computation and analysis of multiple structural change”, Journal of Applied Econometrics 18, 1-22
- Bai, J., Perron, P., 2003b. “Critical values for multiple structural change tests”, Econometrics Journal (2003), volume 6, pp. 72–78
- Bai, J., Perron, P., 2006. "Multiple Structural Change Models: A Simulation Analysis," in Econometric Theory and Practice: Frontiers of Analysis and Applied Research, D. Corbea, S. Durlauf and B. E. Hansen (eds.), Cambridge University Press, 2006, 212-237.
- Bauwens, L., Laurent, S., Rombouts, J.V.K., 2006. “Multivariate GARCH models: A survey”. Journal of Applied Econometrics. 21: 79–109 (2006)
- Ben-Gal I., 2005. “Outlier detection”, in Data Mining and Knowledge Discovery Handbook: A Complete Guide for Practitioners and Researchers, Maimon O. and Rockach L. (Eds.), Kluwer Academic Publishers, 2005, 1-16.
- Bollerslev T., 1986. “Generalized autoregressive conditional heteroskedasticity”, Journal of Econometrics 31: 307–327.
- Burnett, J.E., Carroll, C., Thistle, P., 1995, “Implications of multiple structural change in event studies”, The Quarterly Review of Economics and Finance, Vol.53, No.4, 467-481.
- Campbell, J.Y., Lettau, M., Malkiel, B.G., Xu, Y., 2001. “Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk”, The Journal of Finance, Volume 56, Issue 1, FEB. 2001
- Chambers, J. M., W. S. Cleveland, B. Kleiner, and P. A. Tukey., 1983. “Graphical Methods for Data Analysis”. Belmont, CA: Wadsworth.
- Charemza , W. W. and Deadman, D.F. , 1999, “ New Directions in Econometric Practice . General to Specific Modeling, Cointegration and Vector Autoregression, 2nd edition , Edward Elgar, Aldershot, UK
- Chatterjee, S., and A. S. Hadi. , 2006. “Regression Analysis by Example”, 4th Ed. New York: Wiley.
- Chiang, T.C., Li,J., 2009 . “The Dynamic Correlation between Stock and Bond Returns: Evidence from the U.S. Market”, http://ssrn.com/abstract=1362225 , (Accessed Aug 7, 2010)

- De Santis, G., Litterman, R., Vesval, A., Winkelmann, K. , 2003. “Covariance matrix estimation”, In: Litterman, R. (Ed.), Modern Investment Management: An Equilibrium Approach. Wiley, London.
- Engle RF., 1982. “Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation”, Econometrica 50: 987–1007.
- Figlewski, S., 1997. “Forecasting volatility”, Financial Markets, Institutions and Instruments, 6, 1−88.
- Foster, D.P., Nelson, D. , 1996. ” Continuous records asymptotic for rolling sample estimates”, Econometrica , Vol.64, No.1, 139-174.
- French, K.R., Schwert, G.W., Stambaugh, R.F., 1987. “Expected stock returns and volatility”, Journal of Financial Economics 19, 3–29.
- Grossman, S.,& O. Hart, 1980. “Takeover bids, the free rider problem, and the theory of the Corporation”, Bell Journal of Economics, 11, 42-64.
- Heckman, James J., 1979. “Sample Selection Bias as a Specification Error”, Econometrica 47(1): 153-161.
- Herzel, S.,& Nord, T., *Stărică* ,C. , 2005. “Why Does the Garch (1, 1) Model Often Fail to Produce Reasonable Longer-Horizon forecasts?” http://129.3.20.41/eps/em/papers/0508/0508003.pdf , (Accessed Nov 20, 2010)
- Hochberg, Y., and A. C. Tamhane, 1987. “Multiple Comparison Procedures”. New York: Wiley.
- Holmén, M., & Nivorozhkin, E., 2010, “Takeover Likelihood, Takeover Premium, and Antitakeover Devices: An Example of Selection Bias at Event Studies”, working Paper, University of Gothenburg.
- Hosmer Jr., D. W., and S. Lemeshow., 2000.” Applied Logistic Regression”, 2nd Ed. New York: Wiley.
- Ismail, Ahmad & Krause, Andreas, 2010.” Determinants of the method of payment in mergers and acquisitions,” The Quarterly Review of Economics and Finance 50 (2010), 471–484
- Jorion, Phillipe., 1995. “Predicting Volatility in the Foreign Exchange Market,” *Journal of Finance*, 2, (June 1995), pp. 507–528.
- Martynova, Marina & Renneboog, Luc, 2008. ” A century of corporate takeovers: What have we learned and where do we stand?”, Journal of Banking & Finance 32 (2008), 2148–2177
- McMillan, D. G., & Speight, A., 2004. “Daily volatility forecasts: Reassessing the performance of GARCH models”, Journal of Forecasting, 23, 449−460.
- McMillan, David .G., Ruiz, Isabel, 2009.” Volatility persistence, long memory and time-varying unconditional mean: Evidence from 10 equity indices,” The Quarterly Review of Economics and Finance, 49 (2009) 578–595
- Merton, R. C. 1980. “On Estimating the Expected Return on the Market.” *Journal of Financial Economics* 8:323–361.
- Mikosch, T., & *Stărică* , C. , 2004a.” Non-stationarities in financial time series, the long range dependence and the IGARCH effects”, Review of Economics and Statistics, 86, 378–390.

- Mikosch, T., & *Stărică*, C. , 2004b. “Changes of structure in financial time series and the GARCH model”, Revstat Statistical Journal, 2, 41–73.
- Morellec , Erwan & Zhdanov, Alexei , 2005. “The Dynamics of Mergers and Acquisitions”, Journal of Financial Economics, Volume 77, Issue 3, September 2005, Pages 649-672
- Pregibon, D., 1979. “Data analytic methods for generalized linear models”, PhD diss., University of Toronto.
- Qiu, T., 2008,”Heteroskedasticity-Autocorrelation Robust Covariance Estimation Under Non-stationary Covariance processes”, http://isites.harvard.edu/fs/docs/icb.topic255713.files/3_17_Qiu.pdf. , (Accessed Dec 16, 2010)
- Schwarz, G., 1978. “Estimating the dimension of a model”. Annals of Statistics 6, 461–464.
- Schwert, G.W., 1989. “Why does stock market volatility change over time?”, Journal of Finance 44, 1115–1153.
- Schwert, G.W., 1990a. “Stock market volatility”, Financial Analysts Journal 46, 23–34.
- Schwert, G.W., 1990b. “Stock volatility and the crash of ’87”, Review of Financial Studies 3, 77–102.
- Schwert, G. W., 1996. "Markup pricing in mergers and acquisitions," Journal of Financial Economics, Elsevier, vol. 41(2), pages 153-192,
- Schwert, G.W., Seguin, P.J., 1991. “Heteroskedasticity in stock returns”, Journal of Finance 45, 1129–1155.
- Shleifer, R., & Vishny, R., 2003. “Stock market driven acquisitions”, Journal of Financial Economics, 70, 295–311.
- *Stărică*, C., and Granger, C., 2005. “Nonstationarities in Stock Returns”, Review of Economics and Statistics, 87, 503-522.
- Sul, D., Phillips, Peter C. B. and Choi, Chi.Y., 2005.” Prewhitening Bias in HAC Estimation”, Oxford Bulletin of Economics and Statistics, 67, 4 (2005) 0305-9049
- Welch, B. L., 1947. “The generalization of ’student’s’ problem when several different population variances are involved”, Biometrika, 34, 28–35.
- Wilcoxon, F., 1945. “Individual comparisons by ranking methods”, Biometrics, 1, 80–83.

Appendix:

Figure 1

A Case of Multiple Shifts in the Correlations between Returns to the Acquirer and Target Shareholders around the Announcement Day

This figure illustrates multiple shifts in the daily moving average correlations between daily log-returns to the target and acquirer shareholders around the public announcement of bid offer (Day=0). This figure shows also daily log-returns to Conexant Systems Inc. (acquirer) and GlobeSpanVirata Inc. (target) shareholders. These firms were merged in a stock swap transaction valued at $933.32 million USD. The deal announced on the 3 December 2003 and consummated on 17 February 2004 (84 trading days after the announcement day).The 222 daily log-returns prior to the announcement day is computed in such a way that almost 30% of total daily correlations located after the announcement day . The Simple Moving Average method uses log-returns to both firms from Day *t-20* to *t* to construct 21-trading-day correlations at Day *t*. The Structural Break Methodology is used to test whether there is (are) shift(s) in the mean of correlation series and to determine the related break(s), if any.

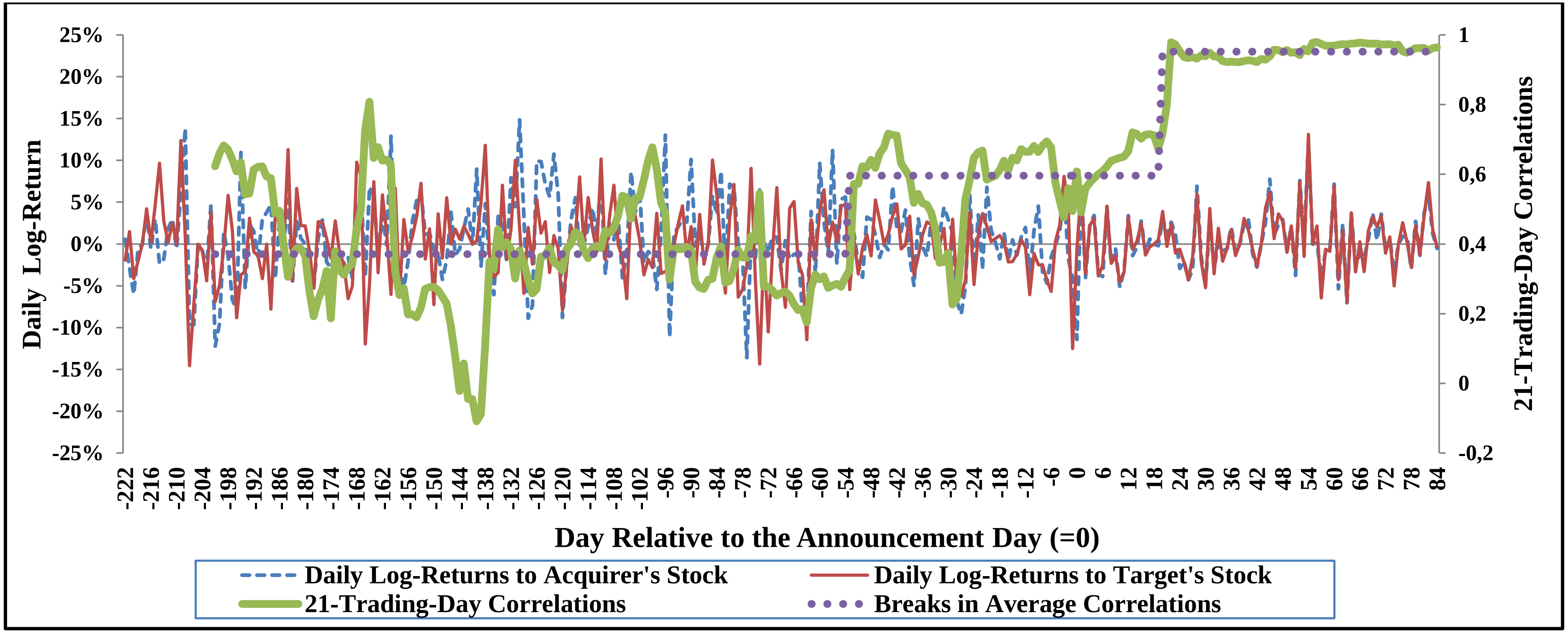

Table 1
Variable list

This table summarizes all variables used in this study together with their explanation. Potential explanatory variables related to deal, pre-deal target and acquire characteristics are used in regressions to describe the dependant variables that are shown in bold. The dependant variables are determined after performing the Structural Break analysis.

Variable	Description
Acquirer and Target Characteristics	
ACQ-Tobin's Q	is equal to the sum of pre-deal (i.e., the last available year) acquirer 's market value of equity and book value of debt minus cash & cash equivalents divided by its book value of total assets.
TARG-Tobin's Q	is equal to the sum of pre-deal (i.e., the last available year) targets 's market value of equity and book value of debt minus cash & cash equivalents divided by its book value of total assets.
ACQ-MV/Turnover	is equal to the sum of pre-deal (i.e., the last available year) acquirer 's market value of equity and book value of debt minus cash & cash equivalents divided by its total turnover (operating revenue).
TARG-MV/Turnover	is equal to the sum of pre-deal (i.e., the last available year) target 's market value of equity and book value of debt minus cash & cash equivalents divided by its total turnover (operating revenue).
ACQ-Size ($m)	is the pre-deal (i.e., the last available year) acquirer 's book value of total assets in Million U.S. Dollars.
TARG-Size ($m)	is the pre-deal (i.e., the last available year) target 's book value of total assets in Million U.S. Dollars.
ACQ-LEV	is equal to the pre-deal (i.e., the last available year) acquirer 's value of total debt divided by its book value of total assets.
TARG-LEV	is equal to the pre-deal (i.e., the last available year) target 's value of total debt divided by its book value of total assets.
REL-Size	is equal to the sum of pre-deal (i.e., the last available year) target 's Market Value of equity and book value of debt minus Cash & Cash equivalents divided by the sum of pre-deal (i.e., the last available year) acquirer 's Market Value of equity and book value of debt minus Cash & Cash equivalents
Deal Characteristics	
Deal-Value ($m)	is the total value paid for acquiring 100% of target shareholdings in Million U.S. Dollars.
ACQ-Announce-Return	is daily log return to the acquirer shareholders at the announcement day of bid offer.
TARG-Announce-Return	is daily log return to the target shareholders at the announcement day of bid offer.
ACQ-Mark-up	is the cumulative (buy-and-hold) log returns to the acquirer's stock from the announcement day of bid offer through delisting of target shares.
TARG-Mark-up	is the cumulative (buy-and-hold) log returns to the target's stock from the announcement day of bid offer through delisting of target shares.

Table 1 (Continued)

Variable	Description
News	is a dummy variable and equals to 1 if the deal, according to the Zephyr database, is rumored in the press, in a company press release or elsewhere prior to the formal offer (announcement) date.
SIC	is a dummy variable and equals to 1 if at least 3 out of the 4 digit of the U.S. Standard Industrial Classification (SIC) code of target and acquirer firms are same.
Cash	is a dummy variable and equals to 1 if the choice of payment form is all-cash to target shareholders.
Equity	is a dummy variable and equals to 1 if the choice of payment form is all-share and the acquirer gives its own share to target shareholders.
Mix	is a dummy variable and equals to 1 if the choice of payment form is a combination of cash and shares to target shareholders.
200i	is a dummy variable and equals to 1 if the initial public bid-offer is announced in the year 200*i* (*i* = 3 , 4 , 5 and 6)
No-Total-Returns	is the number of daily log returns computed for both target and acquirer.
No-Corr	is the total number of daily correlation between daily log returns to the target and acquirer shareholders.
No-Obs-Aft-C	is the number of daily log returns(or daily correlations) available to the target's stock from the announcement day of bid offer through delisting of target shares.
Structural Break Characteristics	
No. Breaks	is a count variable(equals to 0, 1 , 2 , 3 , 4 and 5) and determines, if any, the number of break(s) in the daily SMA correlations between daily log-returns to the target and acquirer shareholders which is estimated by Structural breaks methodology.
Prior-Break-Dummy	is a dummy variable and equals to 1 if there is at least one break prior to the announcement day.
After-Break-Dummy	is a dummy variable and equals to 1 if there is a break after the announcement day.
ith-Break -Prior	is the *i* th break date (in trading days) prior to the announcement day (*i* th = 1st , 2nd , 3rd and 4th).
Break -After	is the date (in trading days) of post-announcement break.
Mean-Corr-Priori	is the mean of correlations in the regime before the *i* th break date prior to the announcement day (*i* = 1 , 2 , 3 and 4).
Mean-Corr-P.Aft	is the mean of correlations in the regime before the post-announcement break date , if any, otherwise it is the mean of correlations in the regime from the first pre-announcement break date to delisting of target 's stock.
Mean-Corr-A.Aft	is the mean of correlations in the regime from the post-announcement break date to delisting of target's stock.
Change-Mean-Corr-Pri	is the change in the mean of correlations due to the first break date prior to the announcement day (i.e., *Mean-Corr-P.Aft - Mean-Corr-Prior*).
Change-Mean-Corr-Aft	is the change in the mean of correlations due to the post-announcement break (i.e., *Mean-Corr-A.Aft - Mean-Corr-P.Aft*).

Table 2

Descriptive Statistics

This table provides information on the descriptive statistics for the 125 deals announced between 2003 and 2006 in the sample and their pre-deal target and acquirer characteristics. The variables listed in this table are used as regressors in the empirical investigations. All variables with their explanations were summarized in Table 1. The sample is split to *Cash*, *Equity* and *Mix* payment subsamples in which there are 54 all-cash, 33 all-equity and 38 mix-payment deals. Mean tested only for the bold variables. Mean and Median difference between variables related to the Acquirer and Target (ACQ - TARG) tested by means of matched-pairs *t*-test and the Wilcoxon matched-pairs signed-ranks test (Wilcoxon 1945), respectively. Whenever the number of observations between variables related to the acquirer and target is not equal, the unpaired and the Welch's (1947) unequal variance options of *t*-test are used. The one-way analysis-of-variance (ANOVA) model is applied for multiple comparison of equality-of-means hypothesis for payment subsamples of a variable (see for example Hochberg et al (1987)). *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

	Variables	Obs.	Mean[1]	Median	Std. Dev.	Min	Max	Difference (ACQ-TARG) *t*-test	Difference (ACQ-TARG) sign-rank test	Mean value of[1] *Cash*	Mean value of[1] *Mix*	Mean value of[1] *Equity*	Multiple mean comparison One-way ANOVA model
Deal characteristics (Continuous variables)	*Deal-Value ($m)*[2]	125	2655.11	428.16	8763.43	52	67000			469.45	3429.68	5339.72	7.34***
	ACQ-Announce-Return	125	**-0.015*** **	-0.008	0.062	-0.245	0.232	-9.76***	-8.08***	**0.003**	**-0.026** **	**-0.033*** **	4.35**
	TARG-Announce-Return	125	**0.119*** **	0.093	0.138	-0.116	0.661			**0.154*** **	**0.113*** **	**0.070*** **	4.04**
	ACQ-Mark-up	125	**0.027**	0.03	0.221	-0.62	1.312	-8.35***	-8.37***	**0.0254**	**0.0126**	**0.0444**	0.18
	TARG-Mark-up	125	**0.2*** **	0.2	0.179	-0.255	0.67			**0.21*** **	**0.195*** **	**0.189*** **	0.16
	No-Total-Obs	125	301.66	270	141.66	123	810			241.41	326.55	371.60	11.03***
	No-Corr	125	279.664	248	141.66	101	788			224.54	304.55	341.21	8.77***
	No-Obs-Aft (C)	125	82.86	73	42.56	28	235			64.56	90.84	103.64	11.17***
Acquirer and Target Characteristics	*ACQ-Tobin's Q*	108	1.66	1.305	1.388	0.065	7.306	-1.41	-1.74*	1.58	1.722	1.712	0.13
	TARG-Tobin's Q	115	2.055	1.414	2.638	0.028	20.558			1.987	1.877	2.384	0.32
	ACQ-MV/Turnover	108	5.085	2.008	21.309	0.065	220.955	0.61	1.59	2.696	9.77	3.28	1.21
	TARG-MV/Turnover	113	3.661	1.605	7.986	0.044	56.405			2.378	3.44	6.093	2.03
	ACQ-Size ($m)[2]	123	10947.21	1831.30	24262.34	26.489	145632	8.51***	9.0***	9916.23	9921.59	13872.7	0.69
	TARG-Size ($m)[2]	123	2782.53	183.15	10981.66	1.571	96531			310.53	3367.45	6277.73	6.21***
	ACQ-LEV	123	0.452	0.463	0.225	0.042	0.997	1.92*	2.31**	0.434	0.44	0.495	0.79
	TARG-LEV	123	0.396	0.343	0.23	0.031	1.027			0.343	0.421	0.457	2.84*
	REL-Size	102	0.515	0.213	1.166	0	9.384			0.197	0.444	1.080	5.37***
Deal characteristics (Binary variables)		Obs.	Proportion						Obs.	Proportion			
	News	125	0.168					*2003*	125	0.216			
	SIC	125	0.576					*2004*	125	0.336			
	Cash	125	0.432					*2005*	125	0.312			
	Equity	125	0.264					*2006*	125	0.136			
	Mix	125	0.304										

[1] Mean tested only for the bold variables.

[2] All tests were based on the natural logarithm of these variables.

Figure 2:

Average Daily Simple Moving Average Correlations (with a Rolling Window of 21-Trading-Day) between Returns to the Acquirer and Target Shareholders, With & Without Announcement Returns

This figure illustrates the influential impact of announcement returns (i.e., outliers) on the average daily SMA correlations between day 0 and day 21. The sample encompasses 125 successful acquisitions and splits to 54 deals that the payment form to the target shareholders is all-Cash, 33 deals with payment in all-Equity and 38 deals with Mix-Payment. For each deal in the sample, the Simple Moving Average(SMA) method uses log-returns to the acquirer and target shareholders from Day *t-20* to *t* to construct 21-trading-day correlations at Day *t* (relative to day 0). The average daily SMA correlation at day t is the average of all SMA correlations at day *t*. Panel A presents average daily SMA correlations for the Sample, All-Cash, All-Equity and Mixed-Payment subsamples while Panel B illustrates the same series by excluding the announcement returns to both firms from the log-return series and SMA analysis. Departring from the announcement day (=0), the sample size is reduced since the number of total daily log-returns is not constant among deals. The average daily correlations are constructed from the full sample around the announcement day (between day -72 to day 28) and from 100 deals at boundary days (-117 and 47) in this figure.

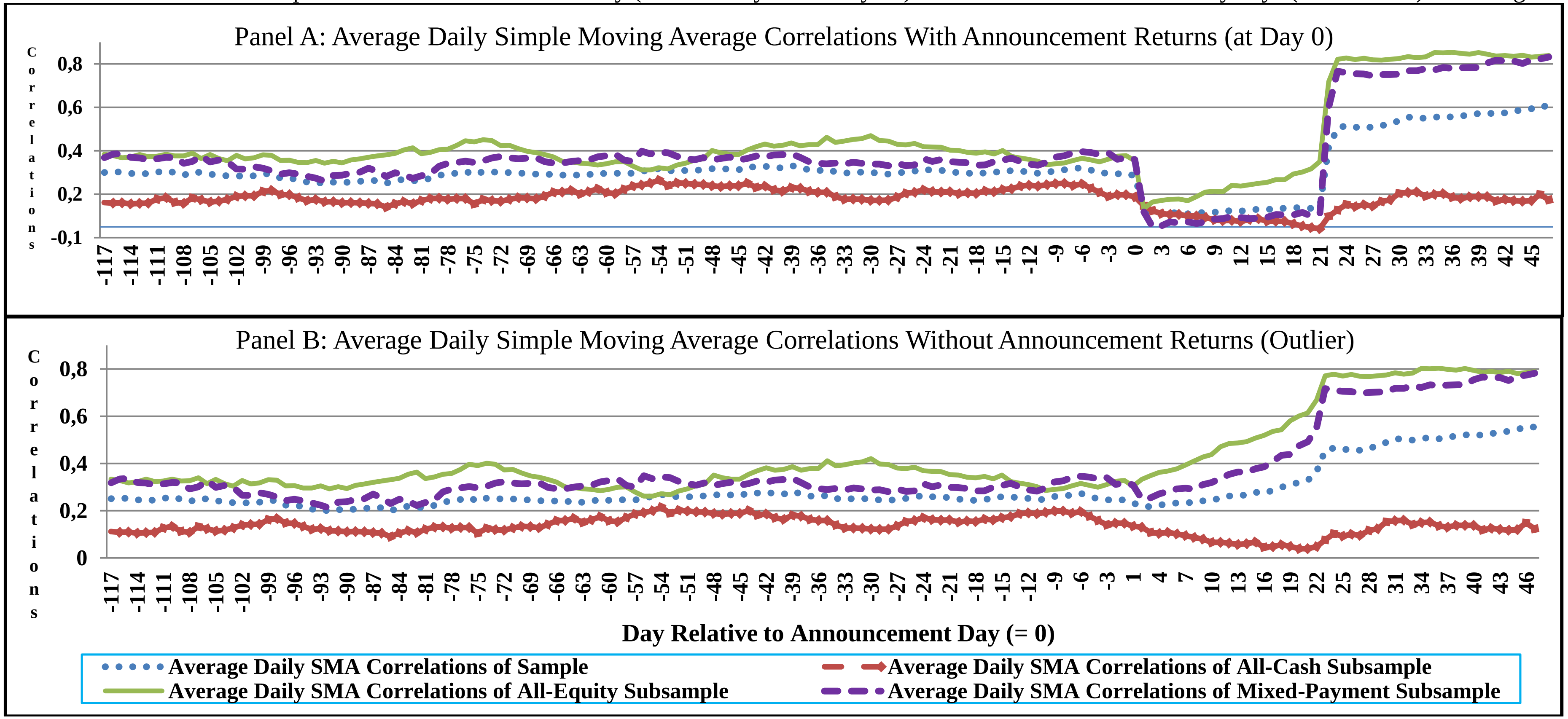

Table 3:

Estimated Multiple Shifts in the Average Daily SMA Correlations for Samples *without* Announcement Returns

This table summarizes the analysis of multiple shifts in the average daily SMA correlations for the main Sample, the All-Cash, the All-Equity and the Mixed-Payment subsamples by excluding the announcement returns to both firms as outliers from the log-return series and SMA analysis. The sample encompasses 125 successful acquisitions and splits to 54 deals that the payment form to the target shareholders is all-Cash, 33 deals with payment in all-Equity and 38 deals with Mix-Payment. All variables with their explanations were summarized in Table 1.

For each deal in the sample, the Simple Moving Average (SMA) method uses log-returns to the acquirer and target shareholders from Day *t-20* to *t* to construct 21-trading-day correlations at Day *t*. The average daily SMA correlation at day *t* is the average of all SMA correlations at day *t.* The average daily correlations are measured from day -117 to day 47(relative to announcement day=0) by using more than 80% of all sample deals. However, main sample is used to find averages around the event day (i.e., between day -72 to day 28).

The structural break methodology developed by Bai and Perron (1998, 2003a) is used to estimate break dates and multiple shifts in the average daily correlations. Up to five break points together with heterogeneous distribution of correlations and residuals across segments are allowed. Andrew's (1991) method is used to construct the HAC standard errors. A trimming factor of 15% is employed which here corresponds to a minimal length of 24 trading days between subsequent breaks. The $SupF_T(\ell+1|\ell)$ test is applied sequentially to estimates the significant number of break dates in the average daily correlations. The OLS is then used to find the mean of average daily SMA correlations in regimes related to the estimated break dates. The unreported *t*-tests indicate that all mean of average correlations are significant at 1% level.
*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Variables	Sample	All-Cash Subsample	All-Equity Subsample	Mixed-Payment Subsample
No.Breaks	2	2	3	4
3rd-Break-Prior				-78
2nd-Break-Prior		-67	-49	-38
1st-Break-Prior	-57	-1	-4	-10
1st-Break-After	22		21	21
Mean-Corr-Prior3				0.273
Mean-Corr-Prior2		0.123	0.323	0.317
Mean-Corr-Prior1	0.235	0.169	0.355	0.295
Mean-Corr-P.Aft1	0.26	0.103	0.44	0.343
Mean-Corr-A.Aft1	0.504		0.781	0.726
$SupF_T(\ell+1\|\ell)$	10.1**	45.3***	8.7734*	19.4***

Table 4:

Summary of the Number and the Location of the Break Dates in the Daily SMA Correlations

This table summarizes the number of multiple shifts in the daily rolling correlations of each deal in the sample based on the Structural Break Methodology (SBM) developed by Bai and Perron (1998, 2003a) and the general location (i.e., timing) of these break dates relative to the takeover announcement day. The sample encompasses 125 successful acquisitions between non-financial exchange-listed U.S. companies from 2003 to 2006. If a deal has break(s) only prior to the announcement day, it is counted in the *Only Breaks at Pre-Announcement* column and if a deal has break(s) only after the announcement day, it is counted in the *Only Breaks at Post-Announcement* column of the following table. Moreover, when a deal have multiple breaks that are distributed both prior and after the announcement date, it is counted in the *Breaks Both at Pre- and Post-Announcement* column.

For each deal in the sample, the Simple Moving Average (SMA) method uses log-returns to the acquirer and target shareholders from Day *t-20* to *t* to construct SMA correlations at Day *t*. The sample size of daily SMA correlations per deal is dependent on the consummation time of each acquisition in the sample.

The algorithm of SBM is allowed to identify maximum five break dates (m=5). Heterogeneous distribution of correlations and residuals across segments, Andrew's (1991) HAC standard errors and a trimming factor of 15% (i.e., ε = 0.15) are applied in construction and critical value of SupF type structural break tests. The statistically significance of $UD\max F_T$ test determines the presence of one break ($m=1$) in the mean of unconditional correlations. For more than one ($m > 1$) breaks, the $SupF_T(\ell+1|\ell)$ test is applied sequentially by using the sequential estimates of the break dates. This sequential approach implies that the number of breaks is equal to m when for the first time the $SupF_T(m+1|m)$ test statistics becomes insignificant. The conventional significance levels (i.e., the 1%, the 2.5%, the 5% and the 10% level) are used in the both aforementioned SupF type tests. The $UD\max F_T$ test determined the number of breaks in only one deal at the 10% significance level and this significance level is used in 17 out of 95 deals in $SupF_T(\ell+1|\ell)$ test in the sample. However, 93.4% of total $UD\max F_T$ tests and 60% of total $SupF_T(\ell+1|\ell)$ tests are statistically significant at the 1% level.

Number of Break Dates Detected	Number of Deals				Total Number of Deals	
	Without Break	Only Breaks at Pre-Announcement	Only Breaks at Post-Announcement	Breaks Both at Pre- and Post-Announcement	Frequency	Precentage
0	4				4	3.2%
1		10	16		26	20.8%
2		4		23	27	21.6%
3		10		28	38	30.4%
4		1		23	24	19.2%
5				6	6	4.8%
Total (Frequency)	4	25	16	80	125	100%
Precentage	3.2%	20%	12.8%	64%	100%	

Figure 3

Frequency Distribution of All Break Dates and the Box Plot of the All, the First Pre-Announcement and the Post-Announcement Break Dates and the Payment Subsamples

Panel A of this figure shows the frequency distribution and the box plot of all break dates in the sample relative to the takeover announcement (day 0). The breaks in the daily rolling (i.e., SMA) correlations of each deal are determined by Structural Break Methodology which are described in the second and third paragraph of Table 4. The sample encompasses 125 successful acquisitions and splits to 54 deals that the payment form to the target shareholders is all-Cash, 33 deals with payment in all-Equity and 38 deals with Mix-Payment. There are 320 shifts in the entire sample. The post-announcement break is observed only in 96 deals of the sample and this number is 105 deals for pre-announcement case. Panel B and C of this figure illustrate the box plot of the distribution of the first-pre-announcement and the post-announcement break dates in the sample and the related payment subsamples. The close and distant hinges of the box plot relative to day 0 correspond to the 1st and 3rd quartile of data, respectively. Moreover, the line and plus sign inside the box plot present the median and mean of data (see; for example, Chambers et al (1983) for more facts about box plots).

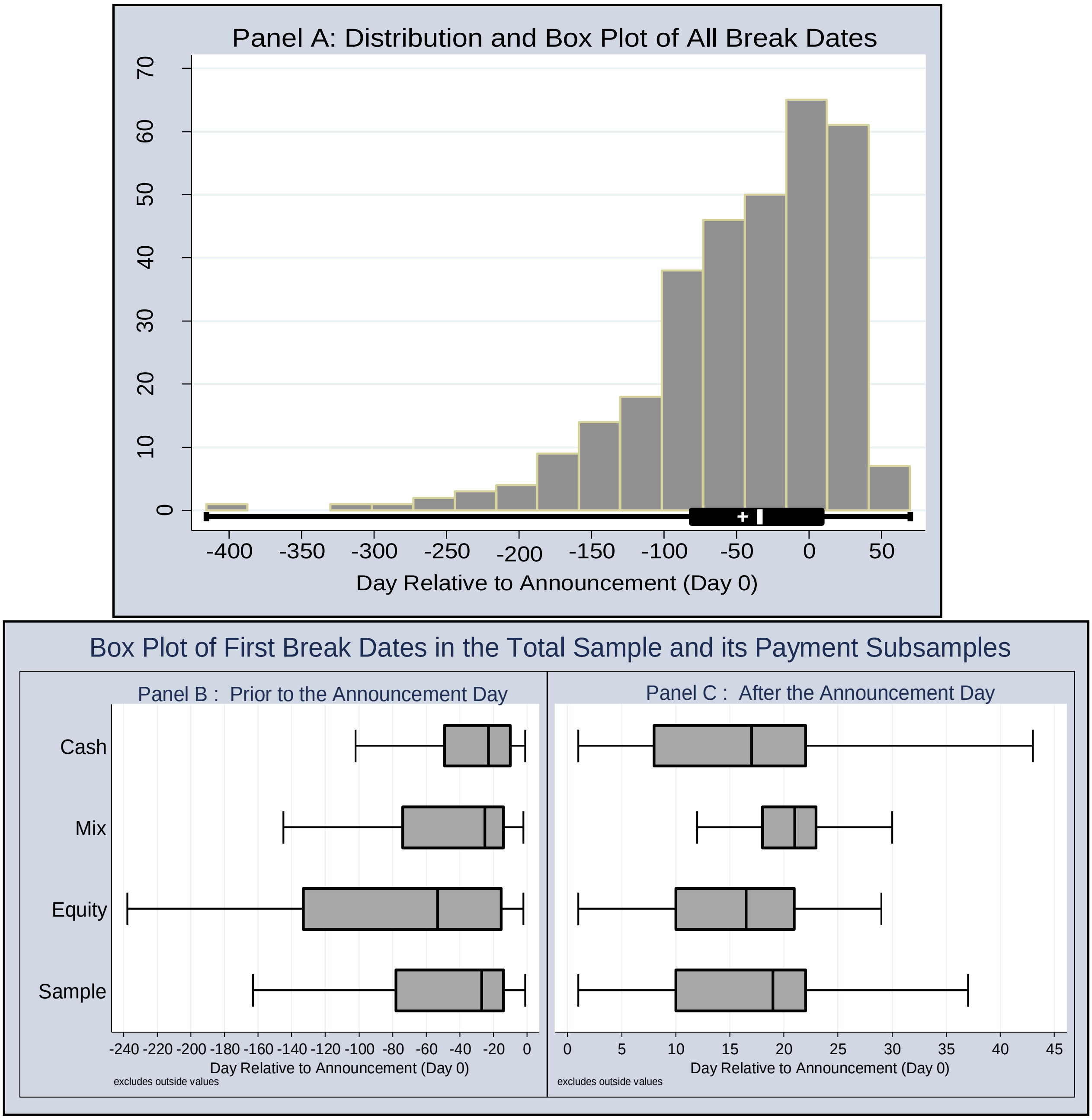

Table 5:

Summary Statistics of the Structural Break Estimates

This table provides summary statistics for the estimates of the Structural Break Methodology (Bai and Perron (1998, 2003a)) which is used to detect multiple shift(s) in the daily SMA correlations of each deal. The sample encompasses 125 successful acquisitions and splits to 54 deals that the payment form to the target shareholders is all-Cash, 33 deals with payment in all-Equity and 38 deals with Mix-Payment. For each deal in the sample, the Simple Moving Average (SMA) method uses log-returns to the acquirer and target shareholders from Day *t-20* to *t* to construct SMA correlations at Day *t*. The sample size of daily SMA correlations per deal is dependent on the consummation time of each acquisition in the sample.

The algorithm of SBM is allowed to identify maximum five break dates (m=5). Heterogeneous distribution of correlations and residuals across segments, Andrew's (1991) HAC standard errors and a trimming factor of 15% (i.e., ε = 0.15) are applied in construction and critical value of SupF type structural break tests. The statistically significance of $UD\max F_T$ test determines the presence of break ($m=1$) in the mean of unconditional correlations. For more than one ($m > 1$) breaks, the $SupF_T(\ell+1|\ell)$ test is applied sequentially by using the sequential estimates of the break dates. This sequential approach implies that the number of breaks is equal to m when for the first time the $SupF_T(m+1|m)$ test statistics becomes insignificant. The conventional significance levels (i.e., the 1%, the 2.5%, the 5% and the 10% level) are used in the both aforementioned SupF type tests.

The $UD\max F_T$ test determined the number of breaks in only one deal at the 10% significance level and this significance level is used in 17 out of 95 deals in $SupF_T(\ell+1|\ell)$ test in the sample. However, 93.4% of total $UD\max F_T$ tests and 60% of total $SupF_T(\ell+1|\ell)$ tests are statistically significant at the 1% level. The OLS is then used to find the mean of daily SMA correlations in regimes related to the estimated break dates.

All variables with their explanations were summarized in Table 1 and those used as dependant variable in the regressions are shown in bold. Mean tested only for the bold variables. The one-way analysis-of-variance (ANOVA) model is applied for multiple comparison of equality-of-means hypothesis for payment subsamples of a variable (see for example Hochberg et al (1987)).

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Variables	*Obs*	*Mean*	*Std. Dev.*	*Min*	*1st Quartile*	*Median*	*3rd Quartile*	*Max*	Mean value of			*Multiple mean comparison ANOVA Model*
									Cash	*Mix*	*Equity*	
No. Breaks	125	***2.56****	1.24	0	2	3	3	5	2.59	2.71	2.33	0.85
Prior-Break-Dummy	125	***0.84****	0.368	0	1	1	1	1	0.833	0.868	0.818	0.18
After-Break-Dummy	125	***0.768****	0.424	0	1	1	1	1	0.630	0.895	0.848	5.55***
4th-Break-Prior	6	-98.5	37.238	-147	-136	-92.5	-72	-51				
3rd-Break-Prior	39	-104.97	75.796	-416	-128	-75	-62	-31				
2nd-Break-Prior	72	-84.6	52.615	-298	-103	-73	-44.5	-21				
1st-Break-Prior	105	-54.42	60.745	-264	-78	-27	-14	-1	-43.4	-47.5	-81.3	3.79**
Break-After	96	18.73	11.72	1	10	19	22	62	18.0	21.6	16.1	1.85
Mean-Corr-Regime-Pri4	6	***0.222****	0.262	-0.087	0.053	0.184	0.322	0.677				
Mean-Corr-Regime-Pri3	39	***0.23****	0.264	-0.318	0.060	0.214	0.414	0.806				
Mean-Corr-Regime-Pri2	72	***0.245****	0.207	-0.298	0.111	0.25	0.361	0.829				
Mean-Corr-Regime-Pri1	105	***0.19****	0.261	-0.281	-0.016	0.163	0.371	0.78	0.12	0.22	0.26	3.01*
Mean-Corr-Regime-P.Aft	121	***0.279****	0.3	-0.313	0.080	0.232	0.499	0.976				
Mean-Corr-Regime-A.Aft	96	***0.544****	0.387	-0.22	0.158	0.592	0.922	0.982				
Change-Mean-Corr-Pri	105	***0.089****	0.323	-0.621	-0.217	0.17	0.315	0.908	0.039	0.142	0.109	1.02
Change-Mean-Corr-Aft	96	***0.269****	0.377	-0.749	0.128	0.313	0.471	0.925	-0.059	0 .433	0.469	34.09***

Table 6:

Estimated Probit models with *Prior-Break-Dummy and After-Break-Dummy as* dependent variables and Estimated Poisson Models with *No. Breaks* as dependent variable

This table provides Probit estimates of the dependences of Likelihood of observing the 1st Pre-announcement break (Panel A), the post-announcement break (Panel B) on the acquirer, target and deal characteristics. Panel C of this table demonstrates the Poisson estimates of the dependence of the number of breaks per deal on the acquirer, target and deal characteristics. The sample encompasses 125 successful acquisitions between non-financial exchange-listed U.S. companies from 2003 to 2006. All variables with their explanations were summarized in Table 1.The Probit and Poisson coefficients are reported with z-statistics and the hereroscedasticity robust *t*-statistics in parentheses. The average marginal effects are computed as means of marginal effects evaluated at each observations of the explanatory variable and reported with z-statistics obtained by the delta standard errors. BIC is the Schwarz (1978) Bayesian Information Criterion and used to choose a parsimonious model. The Wald test is used to examine the joint insignificance of the irrelevant variables in Model 1. The more parsimonious model (Model 2) is thus constructed by excluding those irrelevant variables. Hosmer-Lemeshow test presents the $\chi 2$ goodness-of-fit test for the fitted model and it is a test of the observed against expected number of responses (Hosmer Jr. and Lemeshow (2000)). Link test (developed by Pregibon (1979)) is used to test that all the relevant explanatory variables are included in the regression and the link function of the outcome variable (i.e., the Normal and Poisson function in the Probit and Poisson regression, respectively) is a linear combination of the regressors. Mean VIF is the average variance inflation factor of all explanatory variables and used to detect multicollinearity in the regression (see Chatterjee and Hadi (2006)). Other statistics are self explanatory. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

		Panel A		Panel B		Panel C	
	Dependant Variable	*Prior-Break-Dummy*		*After-Break-Dummy*		*No. Breaks*	
		Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
	Independent Variables	Probit coefficient (*t* -statistic) Average marginal effects		Probit coefficient (*t* -statistic) Average marginal effects		Poisson coefficient (*t* -statistic) Average marginal effects	
	Constant	-1.2959	-1.0289	0.4783	0.4319	0.4708	0.485*
		(-1.25)	(-1.12)	(0.46)	(0.78)	(1.39)	(1.71)
Acquirer and Target Characteristics	*ACQ-Tobin's Q*	0.1476	0.1069	-0.1042		0.0375	0.0455
		(1.14)	(0.88)	(-0.76)		(0.95)	(1.41)
		0.0275	0.0199	-0.0234		0.097	0.1177
	TARG-Tobin's Q	0.1863	0.2308*	0.2525*	0.2134*	0.0302	0.0272
		(1.00)	(1.87)	(1.85)	(1.89)	(1.22)	(1.47)
		0.0347	0.0429*	0.0566*	0.0493*	0.0781	0.0703
	ACQ-MV/ Turnover	-0.0061		0.0723	0.0613	0.0003	
		(-0.83)		(0.88)	(1.02)	(0.21)	
		-0.0011		0.0162	0.0141	0.0008	
	TARG-MV/ Turnover	0.0447		-0.044**	-0.0382**	0.0056	0.0054*
		(0.95)		(-2.52)	(-2.35)	(1.15)	(1.88)
		0.0083		-0.0099***	-0.0088**	0.0145	0.0139*
	Ln (ACQ-Size)	0.2163*	0.1756*	0.106		0.0629**	0.0538**
		(1.72)	(1.73)	(0.77)		(1.99)	(2.35)
		0.0403*	0.0326*	0.0238		0.1628**	0.1391**
	Ln (TARG-Size)	-0.0479					
		(-0.32)					
		-0.0089					
	ACQ-LEV	0.4872		-0.7018		-0.2609	
		(0.50)		(-0.75)		(-0.95)	
		0.0907		-0.1574		-0.6752	
	TARG-LEV	-0.2853		-0.0614		0.1878	0.1737
		(-0.33)		(-0.07)		(0.74)	(0.83)
		-0.0531		-0.0138		0.486	0.4496
	REL-Size	-0.356*	-0.311**	0.0129		-0.0952**	-0.104***
		(-1.83)	(-2.03)	(0.06)		(-2.08)	(-2.76)
		-0.0663*	-0.0578**	0.0029		-0.2464**	-0.269***

Table 6 (Continued)

	Dependant Variable	*Prior-Break-Dummy*		*After-Break-Dummy*		*No. Breaks*	
	Independent Variables	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Deal Characteristics	*Ln (Deal-Value)*			-0.09 (-0.51) -0.0202		0.0175 (0.52) 0.0453	
	ACQ-Announce-Return			1.0928 (0.37) 0.2451		0.4427 (0.48) 1.1455	
	TARG-Announce-Return			-1.5819 (-1.20) -0.3548	-1.5207 (-1.32) -0.3511	-0.1415 (-0.32) -0.3662	
	ACQ-Mark-up			-1.6791* (-1.87) -0.3766*	-1.4025** (-2.13) -0.3238**	-0.257 (-0.93) -0.6649	-0.193 (-0.98) -0.4995
	TARG-Mark-up			-0.1426 (-0.12) -0.032		-0.0528 (-0.15) -0.1367	
	News	0.3486 (0.61) 0.0649		-0.0075 (-0.01) -0.0017		-0.1112 (-0.77) -0.2876	
	SIC	0.7609* (1.88) 0.1417*	0.7606** (2.27) 0.1413**	0.5502* (1.67) 0.1234*	0.4917 (1.56) 0.1135	0.2443** (2.40) 0.6322**	0.2442** (2.54) 0.6319***
	Cash			-0.7344* (-1.82) -0.1647*	-0.5799* (-1.65) -0.1339*	-0.0766 (-0.74) -0.1981	
	Equity	0.3435 (0.67) 0.064		-0.0765 (-0.16) -0.0172		-0.0615 (-0.45) -0.1591	
	Mix	0.2492 (0.59) 0.0464					
	2003	0.5739 (0.93) 0.1069	0.6356 (1.14) 0.118	0.0953 (0.15) 0.0214		0.1155 (0.61) 0.2988	
	2004	0.8667 (1.62) 0.1614*	0.8944* (1.92) 0.1661**	0.2077 (0.39) 0.0466		0.0804 (0.49) 0.208	
	2005	0.2616 (0.50) 0.0487	0.4303 (0.91) 0.0799	0.1762 (0.32) 0.0395		0.0022 (0.01) 0.0057	
	No-Corr	-0.0018 (-1.44) -0.0003	-0.0015 (-1.36) -0.0003	0.0017 (1.15) 0.0004	0.0012 (0.91) 0.0003	-0.0008** (-2.13) -0.0022**	-0.0009** (-2.46) -0.0022**
Regression & Model Specification	Observations	97	100	97	97	97	97
	Log - Likelihood	-33.0728	-34.2039	-39.2868	-40.2694	-157.0332	-158.0418
	Wald Test ($P > \chi^2$)	0.0494**	0.0018***	0.0418**	0.0049***	0.0000***	0.0000***
	Pseudo R^2	0.2386	0.2221	0.2041	0.1842	0.0482	0.0421
	BIC	148.49	114.46	179.22	121.71	414.71	361.83
Robustness Tests	Wald test for joint significance of excluded ($P > \chi^2$)		0.9796		0.9997		0.9372
	Hosmer-Lemeshow Goodness-of-fit test ($P > \chi^2$)	0.1332	0.2675	0.9006	0.7366	0.9953[1]	0.9997[1]
	Link test for Significance of Potential Omitted Predictors (P > |z|)	0.476	0.363	0.665	0.962	0.995	0.581
	Mean VIF	6.77	3.06	7.06	1.74	7.06	3.44

[1] based on the Pearson Goodness-of-fit test statistic

Table 7:

Comparison of Descriptive Statistics between Estimates of Multiple Shifts in the Daily SMA Correlations: *With* and *Without* Announcement Returns in the SMA Rolls

This table provides descriptive statistics for the estimates of multiple shifts in the daily SMA correlations based on two different approaches in modeling the daily SMA correlation series: *with* (Panel B) and *without* (Panel A) inclusion of announcement returns to the pair-firms in the SMA rolls. The sample encompasses 125 successful acquisitions between non-financial exchange-listed U.S. companies from 2003 to 2006. The Structural Break Methodology (Bai and Perron (1998, 2003a)) is used to detect multiple shift(s) in the both of alternative daily SMA correlations of each deal. For each deal in the sample, the Simple Moving Average (SMA) method uses log-returns to the acquirer and target shareholders from Day *t-20* to *t* to construct SMA correlations at Day *t*. In the *without* case, the log-returns at announcement day to the acquirer and target shareholders are excluded from the SMA rolls that use these returns at day 0.The sample size of daily SMA correlations per deal is dependent on the consummation time of each acquisition in the sample. All variables with their explanations were summarized in Table 1 and those used as dependant variable in the regressions are shown in bold. For more details how the Structural Break Methodology is applied here, see notes of Table 5 (the second paragraph).

Mean and Median difference between variables related to both of alternative approaches (*Without* - *With*) tested by means of matched-pairs *t*-test and the Wilcoxon matched-pairs signed-ranks test (Wilcoxon 1945), respectively. Whenever the number of observations between variables among alternative approaches is not equal, the unpaired and the Welch's (1947) unequal variance options of *t*-test are used. Two-sample test of proportion is applied to detect difference between binary outcome variables. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

	Panel A : Multiple Shifts in the Daily SMA Correlations *Without* *Announcement Returns*			**Panel B :** Multiple Shifts in the Daily SMA Correlations *With* *Announcement Returns*			Difference (*Witout* - *With*)		
Variables	**Obs**	**Mean**	**Median**	**Obs**	**Mean**	**Median**	**t-test**	**Sign-rank test Prob > |z|**	**Proportion test Prob > |z|**
No.Breaks	125	2.56	3	125	2.616	3	-0.76	-1.34	
Prior-Break-Dummy	125	0.84	1	125	0.832	1			0.17
After-Break-Dummy	125	0.768	1	125	0.8	1			-0.61
1st-Break-Prior	105	-54.42	-27	104	-48.15	-24.5	-0.74	-2.37**	
Break-After	96	18.73	19	100	19.68	21	-0.54	-2.31**	
Change-Mean-Corr-Pri	105	0.089	0.17	104	-0.042	-0.167	2.70***	2.19**	
Change-Mean-Corr-Aft	96	0.269	0.313	100	0.342	0.417	-1.15	-3.24***	