Paper prepared for the 2011 NZAE Meetings
Wellington, NZ, 29 June – 1 July

ONE FOR ALL OR ALL FOR ONE?
USING MULTIPLE-LISTING INFORMATION IN EVENT STUDIES

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June 4, 2011

Preliminary and incomplete.
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ACKNOLEDGMENTS: We are grateful for helpful comments on a previous version of this paper to seminar participants at Fudan University and the 2010 New Zealand Finance Colloquium. Gu received valuable financial support from the University of Canterbury Friendship City Doctoral Scholarship.

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Abstract

In an event study where at least some of the sample firms have their equity securities listed in more than one market, the question arises as to which is the most appropriate market (or markets) to use for the purpose of estimating average abnormal returns. When arbitrage activity across these markets is restricted in some way, estimating abnormal returns from just one of the listings potentially throws away valuable information. On the other hand, indiscriminate pooling is likely to result in the same information being counted more than once. We propose a simple solution to this problem that (i) uses all the information available from multiple listings, (ii) 'downweights' listing observations that provide little new information, and (iii) yields consistent and efficient abnormal return estimates. Finally, we apply this generalized approach to a unique sample of Chinese foreign mergers and acquisitions and compare the results with those from other approaches that have appeared in the literature.

JEL classification: C12, G14, G15, G34

Keywords: event study; multiple listings; mergers and acquisitions, China

1. INTRODUCTION

The event study has proven to be an indispensable tool for empirical researchers in a wide range of disciplines, particularly corporate finance. Initially applied to single-country, advanced-economy settings, more recently it has extended its domain to studies of multiple and emerging markets.[1] While doing so opens up valuable opportunities for researchers, it also raises a number of questions about the applicability of the original methods to these wider settings.

The particular question we address in this paper concerns the treatment of firms whose securities are listed in multiple countries. The standard event study estimates the average abnormal stock price reaction of a sample of firms subject to the event of interest. However, this procedure is no longer uniquely defined when at least some of the sample firms have their equity securities listed in more than one market. The question then arises as to which is the most appropriate market (or markets) for the estimation of average abnormal returns. This question is potentially important. As of May 2010, approximately a third of the firms appearing in Datastream were listed in at least two markets.[2]

A variety of approaches to this issue have appeared in the literature. The most common is to use returns from each firm's home market, e.g., Aktas, de Bodt and Roll (2004), Bailey, Karolyi and Salva (2006), Beitel, Schiereck and Wahrenburg (2004), Doidge (2004), Ekkayokkaya, Holmes and Paudyal (2009), Faccio, McConnell and Stolin (2006), Keloharju, Knüpfer and Torstila (2008), Kim (2003), and Wang and Boateng (2007). Others, such as Aybar and Ficici (2009) and Campbell, Cowan and Salotti (2009) use returns from

[1] See, for example, Table 1 of Campbell, Cowan and Salotti (2009).
[2] See also Karolyi (2006) for detailed evidence on the increasing importance of multiple listings, and the reasons for why this occurs.

the firm's 'primary' (highest volume) market.[3] Chan, Cheung and Wong (2002) employ the firm's United States market returns.[4]

One feature common to all these studies is that none explicitly discusses, or even mentions, choice of which market listing to use in the estimation of abnormal returns. Presumably this reflects an implicit assumption that arbitrage across markets is unrestricted, so that inter-market price deviations are small and transitory, hence rendering the choice of listing irrelevant to abnormal returns estimation. Put another way, unrestricted arbitrage activity ensures that all listings of a firm's securities quickly reveal the same information, and hence the event study researcher can safely use any one (and only one) of these listings when estimating the firm's event-period abnormal returns.

However, although several studies support the price parity view for developed markets (e.g., Kato, Linn and Schallheim, 1991; Eun and Sabherwal, 2003; Grammig, Melvin and Schlag, 2005), more recent work, which typically includes data from emerging markets, often uncovers significant deviations from parity. For example, Gagnon and Karolyi (2009) report that while most deviations between American Depository Receipt prices and home country prices are significantly less than 100 basis points, the discrepancy can in some cases exceed 50 *percent*. In the same vein, Blouin, Hail and Yetman (2009) find that cross-country price deviations are low if and only if arbitrage costs are low. Finally, in single-country studies, Melvin (2003), Rabinovitch, Silva and Susmel (2003), and Chen, Li and Wu (2010) all report significant deviations from parity for stocks from Argentina, Chile and China respectively.[5]

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[3] Campbell, Cowan and Salotti (2009) utilize data from all listings in their simulation work, but only 'primary' market data in their actual event study. We are grateful to Valentina Salotti for clarifying this point.
[4] Still other studies, such as Amihud, DeLong and Saunders (2002), Anand, Capron and Mitchell (2005), and Ma, Pagán and Chu (2009), provide little indication of how they proceed in this area, although it seems likely that they use home market returns.
[5] See the discussion in Gagnon and Karolyi (2009) for possible causes of incomplete arbitrage across markets, and Chan, Menkveld and Yang (2008) for a specific demonstration.

Together, these results cast some doubt on the usual event study practice of using returns from a single listing for each firm. In general, investors in different markets possess different information sets and hence, left to their own devices, are likely to respond differently to a given event. If arbitrage is unable to aggregate these multiple responses, then the use of a single listing (for a firm that is multi-listed) yields abnormal return estimates that are incomplete in the sense that they ignore important information embedded in the price responses observed in other markets. In such circumstances, using returns from all markets in which each firm's securities are listed not only increases the sample size (often an important consideration when undertaking event studies in emerging markets), but also enables 'full-information' abnormal return estimates to be obtained. On the other hand, of course, to the extent that price responses in different markets are not independent, simple pooling of multi-listing data involves multiple counting of the same information. What is required is a method that extracts the independent information from each listing while counting the common information only once.

In this paper, we outline a simple procedure that achieves this twin objective and yields consistent and efficient estimates of abnormal returns. In the next section, we describe this 'generalized' approach in detail and then, in Section 3, illustrate its use by applying it to a sample of foreign mergers and acquisitions by Chinese firms. Section 4 provides some concluding remarks.

2. A GENERALIZED METHODOLOGY FOR EXTENDING EVENT STUDY ANALYSIS TO THE CASE OF MULTIPLE-LISTINGS

2.1 Benchmark Case: Single-Market Listing of Securities When Errors are Homoskedastic and Cross-Sectionally Independent

Consider initially the benchmark case where all firms in the event data sample are listed on a single stock exchange. This is the situation envisaged in standard event study analysis. We briefly outline the mechanics of that analysis in order to facilitate extension to the more general cases considered below.

Let daily (adjusted) stock prices for each OMA event/firm i at time t be given by P_{it} , and let daily returns be computed by taking the log of stock prices (Strong 1992):

(1) $$R_{it} = ln\left(\frac{P_{it}}{P_{i,t-1}}\right), i=1,2,\ldots,N;$$

where N is the total number of OMA events/firms in the sample, and t is measured relative to a given announcement day: The announcement day is indicated by $t=0$. Days preceding (following) the announcement day are designated by negative (positive) time values.

The following "market model" specification (Brown and Warner, 1985; Strong, 1992) is estimated for each event/firm i at some point previous to the announcement over an estimation period of length S days:

(2) $$R_{it} = \alpha_i + \beta_i R_{mt} + error_{it},$$

where R_{mt} is the return of the local market index at time t.

A test period is chosen to include the announcement day, plus days on either side of $t=0$ to capture lead and lagged effects. The regression results for the market model are used to calculate predicted returns for the test period:

(3) $$\hat{R}_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{mt},$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated values of α_i and β_i from Equation (2). "Abnormal returns" are calculated as the difference between actual returns during the test period and their predicted values (based on the coefficients estimated during the estimation period),

(4) $$AR_{it} = R_{it} - \hat{R}_{it}.$$

We assume the AR_{it} are independent and normally distributed with a mean of 0 and a standard deviation σ. Let the DGP associated with individual AR_{it} observations at time *t* be given by the following equation:

(5) $\boldsymbol{y}_t = \boldsymbol{x}_t \beta + \boldsymbol{\varepsilon}_t$,

where $\boldsymbol{y}_t$ is an $N \times 1$ vector of abnormal returns, AR_{it}, $i = 1,2,...,N$; $\boldsymbol{x}_t$ is an $N \times 1$ vector of ones; β is a scalar representing the mean of the distribution of abnormal returns; and $\boldsymbol{\varepsilon}_t$ is an $N \times 1$ vector of error terms, $\boldsymbol{\varepsilon} \sim N\left(\boldsymbol{0}_N, \sigma^2 \boldsymbol{I}_N\right)$, $\boldsymbol{0}_N$ is an $N \times 1$ vector of zeroes, and $\boldsymbol{I}_N$ is the $N \times N$ identity matrix.

In this case, the OLS estimate of β, $\hat{\beta}_{OLS}$, is efficient:

(6) $\hat{\beta}_{OLS} = \left(\boldsymbol{x}_t' \boldsymbol{x}_t\right)^{-1} \boldsymbol{x}_t' \boldsymbol{y}_t$.

It is easily shown that

(6’) $$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^{N} AR_{it}}{N} \equiv AAR_t,$$

where AAR_t is the “average abnormal return” across the *N* firms at time *t*.

If σ^2 is known, then

(7.1) $Var(\hat{\beta}_{OLS}) = \sigma^2 \left(\boldsymbol{x}_t' \boldsymbol{x}_t\right)^{-1}$, and

(7.2) $s.e.(\hat{\beta}_{OLS}) = \sqrt{\sigma^2 \left(\boldsymbol{x}_t' \boldsymbol{x}_t\right)^{-1}}$.

The latter is easily shown to be equivalent to

(7.2’) $$s.e.(\hat{\beta}_{OLS}) = \frac{\sigma}{\sqrt{N}}.$$

To test the null hypothesis that $\beta = 0$, one forms the Z statistic,

(8) $$Z_t = \frac{\hat{\beta}_{OLS}}{s.e.(\hat{\beta}_{OLS})} = \frac{\left(\boldsymbol{x}_t' \boldsymbol{x}_t\right)^{-1} \boldsymbol{x}_t' \boldsymbol{y}_t}{\sqrt{\sigma^2 \left(\boldsymbol{x}_t' \boldsymbol{x}_t\right)^{-1}}}.$$

This is easily shown to be equivalent to

(8’) $$Z_t = \frac{\sqrt{(\boldsymbol{x}_t'\boldsymbol{x}_t)^{-1}}\,\boldsymbol{x}_t'\boldsymbol{y}_t}{\sigma} = \frac{\sum_{i=1}^{N}\left({AR_{it}}\big/{\sigma} \right)}{\sqrt{N}}).$$

If σ^2 is unknown, we can estimate it by $\hat{\sigma}^2 = \frac{\sum_{s=1}^{S}\sum_{i=1}^{N}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{N(S - 2)}$. Then σ is replaced with $\hat{\sigma}$, in (5)/(5’), and critical t-values (instead of Z-values) are used for hypothesis testing.

The preceding analysis considers the case where abnormal returns are tested on only one day. But suppose there are multiple periods for the testing interval, $t=T_1, T_1+1,\ldots,0,\ldots,T_2$? The extension is straightforward. Redefine the above such that

(9) $$\boldsymbol{y}_T = \boldsymbol{x}_T\beta + \boldsymbol{\varepsilon}_T ,$$

where $\boldsymbol{y}_T$ is an $N(T_2\text{-}T_1+1)\times 1$ vector of abnormal returns, AR_{it}, $i = 1,2,\ldots,N$, $t = T_1, T_1,+1\ldots,T_2$; $\boldsymbol{x}_T$ is an $N(T_2\text{-}T_1+1)\times 1$ vector of ones, β is a scalar that equals the mean of the distribution of abnormal returns, $\boldsymbol{\varepsilon}$ is an $N(T_2\text{-}T_1+1)\times 1$ vector of error terms, $\boldsymbol{\varepsilon} \sim N\left(\boldsymbol{0}_{N(T_2-T_1+1)}, \sigma^2\boldsymbol{I}_{N(T_2-T_1+1)}\right)$, $\boldsymbol{0}_{N(T_2-T_1+1)}$ is an $N(T_2\text{-}T_1+1)\times 1$ vector of zeroes, and $\boldsymbol{I}_{N(T_2-T_1+1)}$ is the identity matrix of order $N(T_2\text{-}T_1+1)$.

Once again, the OLS estimate of β, $\hat{\beta}_{OLS}$, is efficient:

(10) $$\hat{\beta}_{OLS} = (\boldsymbol{x}_T'\boldsymbol{x}_T)^{-1}\boldsymbol{x}_T'\boldsymbol{y}_T ,$$

which is equivalent to

(10’) $$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^{N}\sum_{t=T_1}^{T_2} AR_{it}}{N(T_2 - T_1 + 1)} = ACAR ,$$

where ACAR is the “average cumulative abnormal returns” over the testing interval (T_1,T_2) and over all N firms.

If σ^2 is known, then

(11.1) $Var(\hat{\beta}_{OLS}) = \sigma^2 \left(\boldsymbol{x}_T' \boldsymbol{x}_T\right)^{-1}$, and

(11.2) $s.e.(\hat{\beta}_{OLS}) = \sqrt{\sigma^2 \left(\boldsymbol{x}_T' \boldsymbol{x}_T\right)^{-1}}$.

The latter is easily shown to be equivalent to

(11.2') $s.e.(\hat{\beta}_{OLS}) = \dfrac{\sigma}{\sqrt{N(T_2 - T_1 + 1)}}$.

The corresponding test statistic is given by

$$(12) \qquad Z_{T_1,T_2} = \frac{\hat{\beta}_{OLS}}{s.e.(\hat{\beta}_{OLS})} = \frac{\left(\boldsymbol{x}_T' \boldsymbol{x}_T\right)^{-1} \boldsymbol{x}_T' \boldsymbol{y}_T}{\sqrt{\sigma^2 \left(\boldsymbol{x}_T' \boldsymbol{x}_T\right)^{-1}}} \ ,$$

which is easily shown to be equivalent to

$$(12') \qquad Z_{T_1,T_2} = \frac{\left(\boldsymbol{x}_T' \boldsymbol{x}_T\right)^{-1} \boldsymbol{x}_T' \boldsymbol{y}_T}{\sigma\sqrt{\left(\boldsymbol{x}_T' \boldsymbol{x}_T\right)^{-1}}} = \frac{\sum_{t=T_1}^{T_2} \sum_{i=1}^{N} \left(AR_{it} / \sigma \right)}{\sqrt{N\left(T_2 - T_1 + 1\right)}}).$$

If σ^2 is unknown, we again estimate it by $\hat{\sigma}^2 = \dfrac{\sum_{s=1}^{S} \sum_{i=1}^{N} \left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{N(S-2)}$ and follow the same procedure as described above.

2.2 Generalisation #1: Single-Market Listing of Securities (Errors are Heteroskedastic but Cross-Sectionally Independent)

We now consider the case where (i) error variances are heteroskedastic and (ii) abnormal returns for the same security are independent across observations. Let the DGP be given by

(13) $\boldsymbol{y}_t = \boldsymbol{x}_t \beta + \boldsymbol{\varepsilon}_t$,

where $\boldsymbol{y}_t$, $\boldsymbol{x}_t$, and β are described as above. Under the assumption that errors are heteroskedastic but cross-sectionally independent, $\boldsymbol{\varepsilon}_t$ is an $N \times 1$ vector of error terms,

$$\boldsymbol{\varepsilon}_t \sim N\left(\boldsymbol{0}_N, \boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \sigma_N^2 \end{bmatrix}\right),$$ where $\boldsymbol{0}_N$ is an $N\times 1$ vector of zeroes and $\boldsymbol{\Omega}$ is the $N\times N$ variance-covariance matrix.

In this case, the OLS estimate of β is inefficient. The source of this inefficiency lies in the fact that OLS gives equal weight to every observation. The solution to this problem is to assign different weights to the individual observations. The estimation procedure that assigns an "efficient" set of weights is called Generalized Least Squares (GLS).

Define a "weighting matrix" $\boldsymbol{P}$, where $\boldsymbol{P}$ is an $N\times N$, symmetric, invertible matrix such that $\boldsymbol{P}'\boldsymbol{P} = \boldsymbol{\Omega}^{-1}$. Given $\boldsymbol{\Omega}$ above, it is easily confirmed that

(14) $$\boldsymbol{P} = \boldsymbol{P}' = \begin{bmatrix} \frac{1}{\sigma_1} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sigma_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \frac{1}{\sigma_N} \end{bmatrix}.$$

Assuming the σ_i^2, $i=1,2,\ldots,N$ are known, the GLS estimator of β given this first generalization is given by

(15) $$\hat{\beta}_{GLS\text{-}1} = \left(\boldsymbol{x}_t'\boldsymbol{\Omega}^{-1}\boldsymbol{x}_t\right)^{-1}\boldsymbol{x}_t'\boldsymbol{\Omega}^{-1}\boldsymbol{y}_t,$$

and the estimated coefficient variance and standard error are given by

(16.1) $$Var\left(\hat{\beta}_{GLS\text{-}1}\right) = \left(\boldsymbol{x}_t'\boldsymbol{\Omega}^{-1}\boldsymbol{x}_t\right)^{-1},$$ and

(16.2) $$s.e.\left(\hat{\beta}_{GLS\text{-}1}\right) = \sqrt{\left(\boldsymbol{x}_t'\boldsymbol{\Omega}^{-1}\boldsymbol{x}_t\right)^{-1}}.$$

Alternatively, define $\tilde{\boldsymbol{x}}_t = \boldsymbol{P}\boldsymbol{x}_t$ and $\tilde{\boldsymbol{y}}_t = \boldsymbol{P}\boldsymbol{y}_t$. Then

(15') $$\hat{\beta}_{GLS\text{-}1} = \left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t,$$

(16.1') $Var\left(\hat{\beta}_{GLS\text{-}1}\right) = \left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}$, and

(16.2') $s.\text{e.}\left(\hat{\beta}_{GLS\text{-}1}\right) = \sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}$.

In other words, $\hat{\beta}_{GLS\text{-}1}$ is identical to OLS applied to this equation: $\tilde{\boldsymbol{y}}_t = \tilde{\boldsymbol{x}}_t\beta + \tilde{\boldsymbol{\varepsilon}}_t$, where $\tilde{\boldsymbol{x}}_t = \boldsymbol{P}\boldsymbol{x}_t$, $\tilde{\boldsymbol{y}}_t = \boldsymbol{P}\boldsymbol{y}_t$, and $\tilde{\boldsymbol{\varepsilon}}_t = \boldsymbol{P}\boldsymbol{\varepsilon}_t$. Note that $\tilde{\boldsymbol{\varepsilon}}_t \sim N\left(\boldsymbol{0}_N, \boldsymbol{P\Omega P'}\right) = N\left(\boldsymbol{0}_N, \boldsymbol{I}_N\right)$.

To test the null hypothesis that $\beta = 0$, one forms the Z statistic,

(17) $$Z_t = \frac{\hat{\beta}_{GLS\text{-}1}}{s.e.(\hat{\beta}_{GLS\text{-}1})} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}}.$$

Interestingly, $Z_t = \frac{\hat{\beta}_{GLS\text{-}1}}{s.e.(\hat{\beta}_{GLS\text{-}1})} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}}$ is *NOT* equal to $Z_{ASAR_t} = \frac{\sum_{i=1}^{N}\left(AR_{it}/\sigma_i\right)}{\sqrt{N}}$, where Z_{ASAR_t} is the test statistic associated with average standardized abnormal returns (ASAR).

We can see this by noting that:

(18) $$Z_{ASAR_t} = \frac{\sum_{i=1}^{N}\left(AR_i/\sigma_i\right)}{\sqrt{N}} = \frac{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}\boldsymbol{x}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}}},$$

but

(19) $$\frac{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}\boldsymbol{x}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}}} \neq \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}},$$

Z_{ASAR_t}, and its multiple-period analog, $Z_{ASCAR_{T1,T2}}$ are commonly used for hypothesis testing of abnormal returns in the presence of heteroskedastic returns (Patell, 1976; Mikkelson & Partch, 1986; Doukas & Travlos, 1988; Aybar & Ficici, 2009). The fact that $Z_{ASAR_t} \neq Z_t$ implies that ASAR and ASCAR are not efficient estimators of β.Thus, $Z_{ASAR_t} \neq Z_t$.

If the σ_i , $i=1,2,...,N$, are unknown, we replace them with their estimates $\hat{\sigma}_i = \frac{\sum_{s=1}^{S}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{S - 2}$, ,$i = 1,2,...N,$ and follow the same procedure as described above, except that we still use Z-critical values because the underlying statistics are based on asymptotic theory. Alternatively, σ_i can be replaced by a time-varying estimate to account for the fact that $\hat{R}_{it}$ in Equation (4) is a prediction made outside the estimation period.[6]

2.3 What Hypothesis Corresponds To Z_{ASAR} and Z_{ASCAR}?

Given the widespread usage of Z_{ASAR_t} and $Z_{ASCAR_{T1,T2}}$, we might ask what hypothesis corresponds to the Z statistic, $Z_{ASAR_t} = \frac{\sum_{i=1}^{N}\left(AR_{it} / \sigma_i \right)}{\sqrt{N}}$? Consider the following regression:

$$(20) \qquad \tilde{\boldsymbol{y}}_t = \boldsymbol{x}_t\gamma + \boldsymbol{\varepsilon}_t ,$$

where $\tilde{\boldsymbol{y}}_t$ is an $N\times 1$ vector of <u>standardized</u> abnormal returns, $\left(\frac{AR_{it}}{\sigma_i}\right)$, $i = 1,2,...,N$; $\boldsymbol{x}_t$ is an $N\times 1$ vector of ones; γ is a scalar that equals the mean of the distribution of <u>standardized</u> abnormal returns; and $\boldsymbol{\varepsilon}_t$ is an $N\times 1$ vector of error terms, $\boldsymbol{\varepsilon}_t \sim N(\boldsymbol{0}_N, \boldsymbol{I}_N)$.

It follows that the OLS estimator of γ is

$$(21) \qquad \hat{\gamma}_{OLS} = \left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1} \boldsymbol{x}_t'\tilde{\boldsymbol{y}}_t ,$$

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[6] A common, time-varying estimator for σ_i is $\hat{\sigma}_{it} = \sqrt{\hat{\sigma}_i^2\left(1+\frac{1}{S}+\frac{(R_{mt}-\bar{R}_m)^2}{\sum_{s=1}^{S}(R_{ms}-\bar{R}_m)^2}\right)}$, where $\hat{\sigma}_i = \frac{\sum_{s=1}^{S}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{S - 2}$ (Patell, 1976; Mikkelson and Partsch, 1986; Doukas and Travlos, 1988).

which is easily shown to be equivalent to $ASAR_t = \frac{\sum_{i=1}^{N}\left(AR_{it} \big/ \sigma_i \right)}{N}$.

The OLS estimate of γ is efficient. Further,

(22.1) $Var(\hat{\gamma}_{OLS}) = \left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}$, and

(22.2) $s.e.(\hat{\gamma}_{OLS}) = \sqrt{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}}$.

The latter is easily shown to be

(22.2') $s.e.(\hat{\gamma}_{OLS}) = \frac{1}{\sqrt{N}}$.

To test the null hypothesis that $\gamma = 0$, one forms the Z statistic,

(23) $$Z = \frac{\hat{\gamma}_{OLS}}{s.e.(\hat{\gamma}_{OLS})} = \frac{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}\boldsymbol{x}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}}}.$$

As was shown above, this is equivalent to $Z_{ASAR_t} = \frac{\sum_{i=1}^{N}\left(AR_{it} \big/ \sigma_i \right)}{\sqrt{N}} = \sqrt{N} \cdot ASAR_t$.

Thus, $Z_{ASAR_t} = \frac{\hat{\gamma}_{OLS}}{s.e.(\hat{\gamma}_{OLS})} = \frac{\sum_{i=1}^{N}\left(AR_{it} \big/ \sigma_i \right)}{\sqrt{N}} = \sqrt{N} \cdot ASAR_t$, corresponds to the null hypothesis, $H_0: \ \gamma = 0$, where γ is the mean of the distribution of <u>standardized</u> abnormal returns, $\frac{AR_{it}}{\sigma_i}$. In contrast, $Z_t = \frac{\hat{\beta}_{GLS\text{-}1}}{s.e.(\hat{\beta}_{GLS\text{-}1})}$, corresponds to the null hypothesis, $H_0: \ \beta = 0$, where β is the mean of the distribution of (unstandardized) abnormal returns, AR_{it}. As γ and β will generally be different, Z_{ASAR_t} and $Z_{ASCAR_{T1,T2}}$ do not test hypotheses about the mean of the distribution of (unstandardized) abnormal returns, which is the usual object of interest.

2.4 Generalisation #2: Listings of Securities in Multiple Markets (Errors Are Heteroskedastic And Cross-Sectionally Correlated)

The preceding case applies straightforwardly to securities listed on multiple markets, as long as each observation is associated with a unique event/firm. But in many cases, firms list in more than one market. As each market may have unique information to offer, we do not want to throw away relevant information by failing to use all available observations. On the other hand, we also don't want to pool them and treat them as independent observations. Once again, the solution to the problem consists of using GLS to estimate mean abnormal returns.

We start off similarly to the heteroskedasticity case, allowing each of the *N* event/firm observations to be characterized by its own variance. The only difference is that we generalize our notation to allow for multiple-listings. Define AR_{ijt} as the abnormal returns from security *i* listed in market *j* at time *t*. Note that this allows the same security to be listed in more than one market at the same time.

Let the DGP of abnormal returns, now AR_{ijt}, be represented by

(24) $$\boldsymbol{y}_t = \boldsymbol{x}_t\beta + \boldsymbol{\varepsilon}_t .$$

It is helpful to visualize this more general problem with a specific example:

$$\boldsymbol{y}_t = \begin{pmatrix} AR_{11t} \\ AR_{12t} \\ AR_{13t} \\ AR_{21t} \\ AR_{23t} \\ AR_{32t} \\ AR_{43t} \end{pmatrix}.$$

In this example, the first security is multi-listed in three markets: markets 1,2,and 3. The second security is listed in two markets: markets 1 and 3. And the last two securities are single-listed. Security 3 is listed in market 2. Security 4 is listed in market 3.

Define $\boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_N^2 \end{bmatrix}$, and $\boldsymbol{P}$ such that $\boldsymbol{P'P} = \boldsymbol{\Omega}^{-1}$. Pre-multiplying (24) by $\boldsymbol{P}$ gives $\boldsymbol{Py}_t = \boldsymbol{Px}_t\boldsymbol{\beta} + \boldsymbol{P\varepsilon}_t$, which can be rewritten as

(25) $\tilde{\boldsymbol{y}}_t = \tilde{\boldsymbol{x}}_t\beta + \tilde{\boldsymbol{\varepsilon}}_t$.

Note that $\tilde{\boldsymbol{y}}_t$ is an $N\times 1$ vector of <u>standardized </u>abnormal returns,

$$\tilde{\boldsymbol{y}}_t = \begin{bmatrix} AR_{11t}/\sigma_{11} \\ AR_{12t}/\sigma_{12} \\ AR_{13t}/\sigma_{13} \\ AR_{21t}/\sigma_{21} \\ AR_{23t}/\sigma_{23} \\ AR_{32t}/\sigma_{32} \\ AR_{43t}/\sigma_{43} \end{bmatrix},$$

and that $\tilde{\boldsymbol{\varepsilon}}_t$ is a vector of standardized error terms. Note further that with heteroskedasticity and no cross-sectional dependence, $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\boldsymbol{0}_N, \boldsymbol{I})$

We now generalize the error variance-covariance matrix to allow for correlated abnormal returns when the same security is listed in more than one market. Let

(26.1) $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\boldsymbol{0}_N, \tilde{\boldsymbol{\Omega}})$, where

(26.2) $$\tilde{\boldsymbol{\Omega}} = \begin{bmatrix} 1 & \rho_{11,12} & \rho_{11,13} & 0 & 0 & 0 & 0 \\ \rho_{12,11} & 1 & \rho_{12,13} & 0 & 0 & 0 & 0 \\ \rho_{13,11} & \rho_{13,12} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \rho_{21,23} & 0 & 0 \\ 0 & 0 & 0 & \rho_{23,21} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

and $\rho_{ij,ik}$ refers to correlations of standardized abnormal returns between multi-listing pairs, AR_{ijt} / σ_{ij} and AR_{ikt} / σ_{ik} .

Assuming the σ_{ij} and $\rho_{ij,ik}$ $i=1,2,\ldots,N$ are known, the GLS estimator of β corresponding to this second generalization is

(27) $\hat{\beta}_{GLS\text{-}2} = \left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t$,

(28.1) $Var\left(\hat{\beta}_{GLS\text{-}2}\right) = \left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}$, and

(28.2) $s.e.\left(\hat{\beta}_{GLS\text{-}2}\right) = \sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}$.

To test the null hypothesis that $\beta = 0$, we form the Z statistic,

(29) $$Z_t = \frac{\hat{\beta}_{GLS\text{-}2}}{s.e.(\hat{\beta}_{GLS\text{-}2})} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}}.$$

If the σ_{ij} , $i=1,2,\ldots,N$, are unknown, we substitute their estimated values, $\hat{\sigma}_{ij}$, $i=1,2,\ldots,N$, in the usual manner. As noted above, time-varying estimates of $\hat{\sigma}_{ij}$ may also be employed. Somewhat more problematic is the estimation of $\tilde{\boldsymbol{\Omega}}$ and $\tilde{\boldsymbol{P}}$.

Estimation of $\tilde{\boldsymbol{\Omega}}$ involves estimating the individual elements $\rho_{ij,ik}$ (see Equation 26.2). To achieve this, we follow a three-step process based on the "studentized" residual (as in "Student" t statistic). Similar to out-of-sample prediction errors, in-sample prediction errors will also have different standard deviations across observations. This is true even when the error terms from the DGP all have the same variances. This will cause the standard deviation estimates used to calculate the AR_{ijt} / σ_{ij} and AR_{ikt} / σ_{ik} terms to be time-varying.

First, we estimate the market model regression for each i and j during the estimation period:

(30) $R_{ijs} = \alpha_{ij} + \beta_{ij} Rm_{js} + \varepsilon_{ijs}$, $s = 1,2,\ldots,S$;

where R_{ijs} is observed returns for security *i* in market *j* at time *s*; and Rm_{js} is observed returns for the market portfolio corresponding to market *j* at time *s*. We note that

(31) $$AR_{ijs} = R_{ijs} - \hat{\alpha}_{ij} - \hat{\beta}_{ij} Rm_{js} = \hat{\varepsilon}_{ijs},$$

where $\hat{\varepsilon}_{ijs}$ is the residual from the estimated market model of Equation (30).

Second, we estimate standard deviations so we can standardize the abnormal returns, AR_{ijt}/σ_{ij} and AR_{ikt}/σ_{ik}. The first step consists of collecting the explanatory variables from Equation (30) in the matrix, $\boldsymbol{X}_{ij}$:

(32) $$\boldsymbol{X}_{ij} = \begin{bmatrix} 1 & Rm_{j1} \\ 1 & Rm_{j1} \\ \vdots & \vdots \\ 1 & Rm_{jS} \end{bmatrix}.$$

We then calculate the "hat" matrix

(33) $$\boldsymbol{H}_{ij} = \boldsymbol{X}_{ij}(\boldsymbol{X}'_{ij}\boldsymbol{X}_{ij})^{-1}\boldsymbol{X}'_{ij}.$$

The standard deviation of the s^{th} residual in the estimated market model of Equation (30) is estimated by

(33) $$\hat{\sigma}_{ijs} = \hat{\sigma}_{ij}\sqrt{1-h_{ij}^{s}}$$

where h_{ij}^{s} is the s^{th} diagonal element of $\boldsymbol{H}_{ij}$, and $\hat{\sigma}_{ij}$ is the standard error of the estimate from the market model regressions of Equation (30).

Third, we estimate $\rho_{ij,ik}$. To do that, we take the standardized abnormal returns for the i^{th} firm in markets *j* and *k* -- $\frac{AR_{ijs}}{\hat{\sigma}_{ij}\sqrt{1-h_{ij}^{s}}}$ and $\frac{AR_{iks}}{\hat{\sigma}_{ik}\sqrt{1-h_{ik}^{s}}}$, $s=1,2,\ldots,S$ -- and calculate the associated sample correlation between the two series.[7] These respective estimates of $\rho_{ij,ik}$ are

[7] We employ "lumped" instead of "trade to trade" returns to calculate daily return correlations because of different holiday distribution among nations or areas.

substituted into Equation (26.2), and $\hat{\beta}_{GLS\text{-}2}$ and $s.\text{e.}\left(\hat{\beta}_{GLS\text{-}2}\right)$ are calculated accordingly (cf. Equations 27 and 28.2). Hypothesis testing proceeds accordingly, with critical values for Z_t (cf. Equation 29) taken from the standard normal distribution because the underlying theory is asymptotic.

To generalize the preceding analysis to testing on the interval (T_1, T_2), define

(34.1) $$\tilde{\boldsymbol{Y}} = \begin{bmatrix} \tilde{\boldsymbol{y}}_{T_1} \\ \tilde{\boldsymbol{y}}_{T_1+1} \\ \vdots \\ \tilde{\boldsymbol{y}}_{T_2} \end{bmatrix},$$

(34.2) $$\tilde{\boldsymbol{X}} = \begin{bmatrix} \tilde{\boldsymbol{x}}_{T_1} \\ \tilde{\boldsymbol{x}}_{T_1+1} \\ \vdots \\ \tilde{\boldsymbol{x}}_{T_2} \end{bmatrix}, \text{ and}$$

(34.3) $$\boldsymbol{\Sigma} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}} & \boldsymbol{0}_{NN} & \cdots & \boldsymbol{0}_{NN} \\ \boldsymbol{0}_{NN} & \tilde{\boldsymbol{\Omega}} & \cdots & \boldsymbol{0}_{NN} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0}_{NN} & \boldsymbol{0}_{NN} & \cdots & \tilde{\boldsymbol{\Omega}} \end{bmatrix},$$

where $\tilde{\boldsymbol{Y}}$ and $\tilde{\boldsymbol{X}}$ are each $N(T_2 - T_1 + 1) \times 1$, $\boldsymbol{0}_{NN}$ is a zero matrix of size $N \times N$, and $\boldsymbol{\Sigma}$ is $N(T_2 - T_1 + 1) \times N(T_2 - T_1 + 1)$.

Then the corresponding GLS estimator of β -- the mean of the distribution of abnormal returns – is

(35) $$\hat{\beta}_{GLS\text{-}2} = \left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{Y}},$$

and the estimated standard error of $\hat{\beta}_{GLS\text{-}2}$ is given by

(36) $$s.\text{e.}\left(\hat{\beta}_{GLS\text{-}2}\right) = \sqrt{\left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}}\right)^{-1}}.$$

To test the null hypothesis that $\beta = 0$, we form the Z statistic,

(37) $$Z_{T1,T2} = \frac{\hat{\beta}_{GLS\text{-}2}}{s.e.(\hat{\beta}_{GLS\text{-}2})} = \frac{\left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{Y}}}{\sqrt{\left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}}\right)^{-1}}}\ .$$

We can simplify this notation considerably (and accordingly facilitate practical estimation). First note that

(38) $$\boldsymbol{\Sigma}^{-1} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}}^{-1} & \boldsymbol{0}_{NN} & \cdots & \boldsymbol{0}_{NN} \\ \boldsymbol{0}_{NN} & \tilde{\boldsymbol{\Omega}}^{-1} & \cdots & \boldsymbol{0}_{NN} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0}_{NN} & \boldsymbol{0}_{NN} & \cdots & \tilde{\boldsymbol{\Omega}}^{-1} \end{bmatrix}.$$

Thus,

(35') $$\hat{\beta}_{GLS\text{-}2} = \left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{Y}} = \left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t\right), \text{ and}$$

(36') $$s.e.\left(\hat{\beta}_{GLS\text{-}2}\right) = \sqrt{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}\ .$$

This leads to the following statistic for multi-period testing of abnormal returns in the presence of both heteroskedasticity and cross-sectional correlation due to multi-listing:

(37') $$Z_{T1,T2} = \frac{\hat{\beta}_{GLS\text{-}2}}{s.e.(\hat{\beta}_{GLS\text{-}2})} = \frac{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t\right)}{\sqrt{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}} = \sqrt{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t\right)\ .$$

The intuition underlying the above procedure is straightforward. Suppose a researcher has, for a given event type, access to data from firms listed in multiple markets (where returns are both heteroskedastic and cross-sectionally correlated). As discussed earlier, pooling the listings without further adjustment would involve what is essentially double-counting of virtually identical observations. Instead, what is required is an appropriate weighting system that incorporates in the abnormal return estimates the different information about wealth effects possessed by the different markets – at the same time counting only once the information that is common across markets. The generalized approach outlined above calculates weights using the error variance-covariance matrix, thus achieving an efficient weighting of individual observations. Note that $\hat{\beta}_{GLS\text{-}2}$, and the corresponding Z_t and $Z_{T1,T2}$ statistics, are designed to estimate and test hypothesis about β, the mean of the population of abnormal returns; and not γ, the mean of the population of standardized abnormal returns.

3. APPLICATION: OVERSEAS MERGERS AND ACQUISITIONS BY CHINESE FIRMS

In this section, we apply the approach described above to a sample of overseas mergers and acquisitions (OMAs) by non-financial Chinese firms between 1 January 1994 and 31 December 2009.[8] There are two reasons why this should be a useful setting for assessing the potential contribution of our generalized methodology. First, the geographical dispersion of OMAs means that information relevant to a particular event is also likely to be dispersed across markets. For example, while mainland investors might be expected to have informational advantages concerning Chinese acquiring firms, foreign investors may be better informed about the overseas targets. Estimation of the total wealth effects emanating from OMAs requires aggregation of these individual-country information sets. Second, such aggregation is unlikely to be revealed by the price reaction in a single market. Prior literature (Chen et al., 2010; Gagnon & Karolyi, 2004) suggests that the Chinese mainland markets are not well integrated with other markets and that deviations from price parity are both common and substantial.

3.1 Summary Information on Multi-listings

To be included in our sample, the acquiring Chinese firm must (i) have its shares listed in at least one of the following exchanges: Shanghai and Shenzhen exchanges (China Mainland), SEHK (Hong Kong, China), NYSE, AMEX or NASDAQ (US); (ii) have stock

[8] The data on OMAs were obtained from Thomson SDC Platinum M&A Database.

price information available from DataStream; and (iii) provide at least 137 days of continuous return data before, and 10 days after, the announcement date, of which fewer than 50% are zero return days. 157 OMA events initiated by a total of 96 Chinese acquirers satisfied these criteria. Over a third of these deals involved target firms located in Hong Kong, with the remainder spread widely across six continents. With Hong Kong excluded, the US is the most frequent location of target firms.[9]

TABLE 1 summarizes the listing status of the Chinese acquiring firms involved in the 157 OMA events. Of these, 111 events involve firms listed in a single market only – 50 in China, 30 in Hong Kong, China and 31 in US. The remaining 46 events are dual-listed (36) or triple-listed (10). In total, there are 213 return reactions in the sample when multi-listings are taken into account. This compares with 64 observations if we restricted ourselves to events listed on Chinese Mainland markets. Of course, the extended sample cannot simply be thought of as providing independent draws from a distribution – 102 of the 213 observations are related, in that they consist of double- or triple-listed shares of the same event/firm.

3.2. Summary Information For Correlations of Abnormal Returns

TABLE 2 summarizes the estimated correlations between standardized abnormal returns for the multi-listed events/firms in our sample (see Section 2.4 for a discussion of how the respective $\rho_{ij,ik}$ terms were estimated). There are 10 pairwise correlations, $\rho_{ij,ik}$, for the China Mainland-US markets, corresponding to 10 events/firms that are jointly listed on the China Mainland and US markets. Likewise, there are 16 pairwise correlations for the China Mainland-Hong Kong markets, and 40 for the Hong Kong-US markets.

The table reports much lower pairwise correlations for abnormal returns associated with shares jointly listed in the China Mainland and overseas markets, than for shares listed

[9] We employ the same OMA event data as we used in Chapter Three. Please see Table 1-3 in Chapter Three for details.

in the Hong Kong and US markets. The mean value of pairwise correlations for the Hong Kong – US markets is 0.609, compared to 0.113 and 0.086 for China Mainland – US and China Mainland – Hong Kong.[10]

The low China Mainland – Hong Kong correlation is noteworthy given that the markets share the same time zone and language, and similar culture. However, shares listed on Chinese Mainland exchanges are not exchangeable with shares of the same firm listed overseas. Further, Chinese citizens are prohibited from investing in Hong Kong or the US. These trading obstacles have been cited as an explanation for the well-known discount of Hong Kong H shares relative to China A shares.[11]

In contrast, the Hong Kong market is generally regarded as being highly integrated with US markets. Hong Kong H-share ADRs in the US, and Pilot program securities in Hong Kong, are both exchangeable. Further, there is no citizenship restriction for mutual investment. As a result, the Hong Kong - US dual-listing pairs achieve relatively high correlations despite the fact that there are significant differences in the closing times of the respective markets, due to the fact that the markets are in different time zones.

This is further evidenced by TABLE 3, which reports mean absolute percentage deviations in (closing) prices between markets for dual-listed shares over the calendar year 2008. The mean, absolute percentage difference iss only 4.8% for Hong Kong – US dual-listed pairs, compared to 40.9% and 47.3% for China Mainland – US and China Mainland –

[10] Empirical studies show that correlation between different markets are pretty low: 0.0071-0.1232 for market return pairs (Yun, Abeyratna, & David, 2005); 0.107-0.403 for monthly returns in Cho et al. (1986); 0.24-0.71 for monthly excess return pairs in Longin & Solnik (1995) and -0.006-0.673 for daily residual returns pairs in Eun & Shim (1989). U.S. and Canada markets are found to get highest correlation, approximately 0.69, whereas U.S. and less developed markets are far less correlated; U.S. stock markets have significant return and volatility spillover effect to other international stock markets, whereas no other markets can significantly explain U.S. market movements (Cheol S. Eun & Shim, 1989; Hamao, Masulis, & Ng, 1990; Yun et al., 2005).

[11] However, HK and U.S. citizens are allowed to purchase Chinese B shares in HK Dollar, US Dollar (T+3). Only Qualified Chinese Domestic Investment Institutions (QDII) can purchase foreign shares in foreign markets with a quota. Of course, there are ways for Chinese citizens to transfer money aboard and invest overseas with the help of financial institutions, or brokers, agencies in grey or black markets even under the capital control environment.

Hong Kong dual-listings.[12] The table also reports individual price deviations for selected multi-listed shares.

Together, TABLES 2 and 3 provide evidence that multi-listed shares are imperfectly correlated and contain useful, independent information that can better inform estimates of market reactions to OMA announcements.

3.3. Comparison of OLS And GLS Estimators

TABLE 4 reports mean abnormal returns for each day of the 21-day test period, (-10,10). One problem with identifying differences in estimation procedures is that one must be careful not to conflate the effect of different sample sizes. For example, GLS results that use multi-listed observations may differ from OLS results based on one observation per event/firm either because of the different estimation procedures, or different datasets, or both. TABLE 4 is designed to help differentiate these effects. We apply OLS and the GLS estimators to estimate mean abnormal returns for each of three datasets: (i) China Mainland listings (64 observations), (ii) "Highest Volume" listings (157 observations), and (iii) All Listings (213) observations. The "Highest Volume" dataset selects only one observation per event/firm, choosing the market where the respective firm's shares have highest trading volume.

We first look at the OLS and GLS-1 results from the sample of 64 mainland listings. The results for the two procedures are very similar. The estimates of the mean value of abnormal returns are approximately the same. Further, both procedures find statistical significance for Day (-1) and Day (2).

We next look at the sample of 157 Highest Volume listings. There include Chinese acquirers who list on all three markets: (i) China Mainland, (ii) Hong Kong, and (iii) the U.S.

[12] We employ US dollar prices and all the time series prices in year 2008 are from DataStream. The formula for mean absolute percentage deviation is: $P_{mapd} = \frac{|p_1 - p_2|}{p_2}$.

The two procedures produce much different results for this sample. The major difference is that OLS finds significant day effects on Day (-5), Day (2), and Day (3). The GLS-1 procedure finds no significant abnormal returns for any of the 21 days of the test period.

For the sample of 213 multi-listings, the three procedures once again produce diverse results. OLS produces significant abnormal returns on Day (-5), Day (0), Day (1), Day (2) and Day (3). This contrasts with the GLS-1 procedure, which finds that abnormal returns are significant only on Day (1). The GLS-2 procedure estimates a significant abnormal return only for Day (-1).

TABLE 5 repeats the comparison, this time focussing on key intervals. Once again, the results differ across datasets and estimation procedures. Interestingly, when it comes to statistical significance, the three procedures produce identical results within each sample, but different results across samples. For the China Mainland dataset, abnormal returns are significant on the (-5,-1) interval. In contrast, for the Highest Volume and All Listings datasets, abnormal returns are only significant on the (-1,1) interval. Across all three samples, the GLS-1 and GLS-2 results estimate mean abnormal returns that are close to each other. The OLS results tend to be substantially larger.

The preceding results provide a range of estimates depending on the dataset and estimation procedure. That leads to the question, which estimate(s) are best? We invoke two principles in our analysis. First, more observations are better. More observations provide more information. Compared to the 64 mainland listings, the 157 Highest Volume listings include some Chinese acquirers who only list on overseas markets. For firms from emerging markets, foreign-listing is a signal of international operations experience, and offers greater transparency and protection for investors. Excluding these firms from an analysis of Chinese OMAs could result in sample selection that biases estimates of the mean of the population distribution of abnormal returns.

Further, expanding the data set from the 157 Highest Volume listings to the All Listings dataset of 213 observations allows better aggregation of different information sets. Because of language, cultural linkages and different geographic distributions, mainland investors are likely to be more knowledgeable about Chinese acquirers, while Hong Kong and US may be better informed about foreign targets. These alternative information sets will be artificially censored if we only allow one market observation for each event/firm. Accordingly, the best overall evaluation of an OMA announcement is the one that utilizes all available information across different information sets.

We see evidence of this in both TABLES 4 and 5 by comparing identical procedures across different datasets. For example, OLS estimates significant abnormal returns for Day (-1) using the China Mainland observations, but not for the Highest Volume and All Listings observations. Alternative, OLS estimates significant abnormal returns on the (-1,1) window for the Highest Volume and All Listings samples, but not for the China Mainland sample. This is evidence that foreign investors differ from Chinese investors in their evaluations of Chinese OMAs. Of course, OLS's assumptions of homoskedasticity and cross-sectional independence across all observations is untenable as one increases the sample size to include multi-listed observations from different markets.

The choice of best sample size leads to the choice of best estimator. The use of multi-listed observations – which is desirable both because it increases sample size and allows a greater range of investor evaluations – argues for the GLS-2 procedure. The other two procedures treat multi-listed observations as though they are independent. TABLE 2 and 3 indicate that this assumption is not warranted, particularly for shares that are dual-listed on the Hong Kong and US share markets.

While the GLS-1 and GLS-2 procedures produce similar interval results for the All Listings dataset, the daily results present somewhat different pictures of market responses to

Chinese OMA announcements. The GLS-1 procedure finds a single, statistically significant daily response on Day (1). In contrast, the GLS-2 procedure estimates a significant market response on Day (-1). In other words, the GLS-1 procedure finds evidence of a market lag to OMA announcements by Chinese acquiring firms. The GLS-2 procedure finds evidence of information leakage. The latter interpretation is arguably more believable when it comes to understanding market reactions to information disclosures.

4. CONCLUSION

This paper extends standard event study analysis to cases where firms list their shares in more than one exchange. These additional listings supply extra information about how investors perceive announcements of firms' policy decisions. In addition, they enable researchers to construct larger samples. The latter can be important when performing event studies of firms from emerging markets where the number of events/firms are often relatively small. Our approach applies generalized least squares (GLS) procedures that explicitly incorporate the relationship of share price performance across multiple exchanges.

Our theoretical development of the GLS procedure allows a direct comparison with conventional approaches that develop sample statistics based on standardized abnormal returns (cf. Mikkelson and Partch, 1986; Doukas & Travlos, 1988; and Aybar and Ficici, 2009). We show that these conventional approaches implicitly test hypotheses about the population of <u>standardized</u> abnormal returns. In contrast, our GLS procedure allows hypotheses to be directly applied to the distribution of (unadjusted) abnormal returns, which is usually the primary subject of interest.

We demonstrate the applicability of our approach by estimating abnormal returns for announcements of overseas mergers and acquisitions (OMAs) by Chinese acquiring firms over the period 1994-2009. Many of the Chinese acquiring firms in our sample list on more than one exchange. Our analysis compares estimates of abnormal returns across three different dataset – China Mainland listings, Highest Volume listings, and All Listings – and across three different estimation procedures (OLS, GLS allowing for event/firm heteroskedasticity, and GLS allowing for both heteroskedasticity and cross-dependent correlation). We demonstrate that the different results obtained by applying GLS to multiple-listed observations is partly due to the inclusion of additional data, and partly due to differences in the estimation procedure. We argue that the best approach when studying firms from emerging markets is one that utilizes price reactions across multiple exchanges and, correspondingly, uses GLS to appropriately address issues of cross-sectional dependence associated with multiple listings. As noted above, approximately a third of the firms appearing in Datastream are listed in at least two markets. The approach developed in this paper allows researchers to exploit the additional information available from these multiple-listed observations.

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TABLE 1

SUMMARY INFORMATION ON MULTI-LISTINGS

LISTING	***NUMBER OF EVENTS***	***NUMBER OF OBSERVATIONS***	***NUMBER OF FIRMS***
China Mainland only	50	50	40
Hong Kong only	30	30	22
U.S. only	31	31	17
China Mainland and Hong Kong	6	12	4
China Mainland and U.S.	0	0	0
Hong Kong and U.S.	30	60	9
China Mainland, Hong Kong and U.S.	10	30	4
TOTAL	157	213	96

TABLE 2
SUMMARY INFORMATION FOR MULTI-LISTING CORRELATIONS

MARKETS	***NUMBER OF CORRELATION TERMS***	***MEAN***	***MAX***	***MIN***
$\boldsymbol{\rho_{ij,ik}}$: ***i* = China Mainland** ***j* = US**	10	0.113	0.404	-0.101
$\boldsymbol{\rho_{ij,ik}}$: ***i* = China Mainland** ***j* = Hong Kong**	16	0.086	0.378	-0.185
$\boldsymbol{\rho_{ij,ik}}$: ***i* = Hong Kong** ***j* = US**	40	0.609	0.879	0.000

NOTE: The numbers in the table summarize the respective $\hat{\rho}_{ij,ik}$ terms used to construct the generalized error variance-covariance matrix, $\tilde{\boldsymbol{\Omega}}$, as specified in Equation 24.2.

TABLE 3

PRICE DISPARITY BETWEEN INDIVIDUAL PAIRS OF MULTI-LISTED SHARES (MEAN ABSOLUTE PERCENTAGE DEVIATION)

CHINA MAINLAND - US		***CHINA MAINLAND – HONG KONG***		***HONG KONG - US***	
China Petrol. & Chem.	0.454	***Sinopec***	0.455	***China Petrol. & Chem.***	0.023
Yanzhou Coal Mining	0.408	***Yanzhou Coal mining***	0.410	***Yanzhou Coal Mining***	0.026
China Life Insurance	0.124	***China Life Insurance***	0.123	***China Life Insurance***	0.022
PetroChina	0.471	***PetroChina***	0.472	***PetroChina***	0.022
		Aluminum Corp. of China	0.508	***China Netcom GP***	0.022
		China Nonferrous Metals	0.985	***China Telecom SR***	0.023
		Angang Steel	0.193	***CNOOC***	0.024
		Huaneng Power Intl.	0.399	***China Resources Ent.***	0.078
				Yuexiu Property	0.912
				China Unic	0.025
				China Mobile	0.021
				Lenovo GP	0.020
MEAN = 0.409		***MEAN*** = 0.473		***MEAN*** = 0.048	
MEDIAN = 0.454		***MEDIAN*** = 0.455		***MEDIAN*** = 0.023	

NOTE: Mean Absolute Percentage Deviation (*MAPD*) between prices p_1 and p_2 is calculated as $MAPD = \frac{|p_1 - p_2|}{p_2}$. All prices are first converted to US dollars. Price series are taken from year 2008 in DataStream.

TABLE 4
DAILY RESULTS COMPARISON

DAY	CHINA MAINLAND (64)		HIGHEST VOLUME (157)		ALL LISTINGS (213)		
	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{GLS-2}$
-10	0.0011 (0.38)	0.0009 (0.40)	0.0026 (0.94)	0.0021 (1.31)	0.0026 (1.19)	0.0018 (1.35)	0.0022 (1.53)
-9	0.0037 (1.35)	0.0022 (0.99)	0.0025 (0.92)	0.0018 (1.16)	0.0026 (1.15)	0.0021 (1.53)	0.0023 (1.59)
-8	0.0018 (0.64)	0.0020 (0.91)	-0.0003 (-0.10)	0.0001 (0.04)	-0.0004 (-0.18)	-0.0003 (-0.23)	-0.0005 (-0.34)
-7	0.0001 (0.02)	-0.0002 (-0.11)	-0.0031 (-1.15)	-0.0012 (-0.76)	-0.0033 (-1.47)	-0.0015 (-1.07)	-0.0001 (-0.08)
-6	0.0005 (0.17)	-0.0010 (-0.44)	-0.0017 (-0.61)	-0.0020 (-1.30)	-0.0012 (-0.54)	-0.0023 (-1.70)	-0.0026 (-1.81)
-5	0.0040 (1.45)	0.0014 (0.64)	0.0061** (2.22)	0.0007 (0.43)	0.0051** (2.27)	0.0006 (0.43)	0.0009 (0.66)
-4	0.0009 (0.32)	0.0030 (1.37)	-0.0023 (-0.85)	0.0022 (1.39)	-0.0015 (-0.65)	0.0013 (0.95)	0.0016 (1.12)
-3	-0.0003 (-0.10)	-0.0001 (-0.06)	0.0000 (0.00)	0.0011 (0.68)	-0.0005 (-0.24)	0.0004 (0.26)	0.0010 (0.66)
-2	0.0016 (0.59)	0.0014 (0.64)	-0.0022 (-0.81)	-0.0006 (-0.40)	-0.0028 (-1.24)	-0.0011 (-0.78)	-0.0012 (-0.80)
-1	0.0087*** (3.18)	0.0062*** (2.82)	0.0036 (1.32)	0.0030 (1.89)	0.0033 (1.49)	0.0022 (1.61)	0.0029** (2.01)
0	0.0003 (0.11)	0.0019 (0.86)	0.0044 (1.61)	0.0017 (1.05)	0.0044** (1.98)	0.0012 (0.91)	0.0011 (0.77)
1	-0.0010 (-0.35)	-0.0019 (-0.85)	0.0040 (1.48)	0.0019 (1.23)	0.0054** (2.43)	0.0031** (2.28)	0.0025 (1.72)
2	-0.0060** (-2.20)	-0.0050** (-2.29)	-0.0059** (-2.17)	-0.0010 (-0.64)	-0.0052** (-2.34)	-0.0013 (-0.96)	-0.0012 (-0.82)
3	0.0002 (0.068)	0.0005 (0.22)	-0.0056** (-2.05)	-0.0021 (-1.34)	-0.0047** (-2.13)	-0.0019 (-1.42)	-0.0024 (-1.65)

DAY	CHINA MAINLAND (64)		HIGHEST VOLUME (157)		ALL LISTINGS (213)		
	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{GLS-2}$
4	-0.0045 (-1.64)	-0.0031 (-1.41)	-0.0024 (-0.86)	-0.0016 (-1.04)	-0.0010 (-0.45)	-0.0008 (-0.59)	-0.0011 (-0.78)
5	0.0038 (1.37)	0.0020 (0.94)	0.0014 (0.50)	0.0014 (0.91)	0.0018 (0.83)	0.0018 (1.33)	0.0015 (1.061)
6	-0.0010 (-0.36)	0.0006 (0.27)	-0.0017 (-0.63)	-0.0012 (-0.77)	0.0000 (-0.01)	-0.0003 (-0.22)	-0.0012 (-0.82)
7	0.0029 (1.06)	0.0019 (0.86)	0.0045 (1.65)	0.0008 (0.48)	0.0034 (1.53)	0.0005 (0.36)	0.0010 (0.69)
8	0.0010 (0.38)	0.0026 (1.21)	0.0005 (0.18)	0.0013 (0.86)	0.0010 (0.43)	0.0012 (0.86)	0.0009 (0.62)
9	-0.0023 (-0.85)	-0.0034 (1.56)	-0.0006 (-0.23)	-0.0015 (-0.98)	-0.0004 (-0.19)	-0.0012 (-0.91)	-0.0011 (-0.80)
10	-0.0034 (-1.24)	-0.0039 (-1.77)	-0.0031 (-1.13)	-0.0018 (-1.15)	-0.0028 (-1.25)	-0.0016 (-1.19)	-0.0014 (-1.00)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS; $\hat{\beta}_{GLS\text{-}1}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for event/firm-specific heteroskedasticity; and $\hat{\beta}_{GLS\text{-}2}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both event/firm-specific heteroskedasticity and cross-sectional dependence arising from multi-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero.

*, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level (two-tailed test).

TABLE 5
INTERVAL RESULTS COMPARISON

INTERVAL	*CHINA MAINLAND (64)*		*HIGHEST VOLUME (157)*		*ALL LISTINGS (213)*		
	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS\text{-}1}$	$\hat{\beta}_{GLS\text{-}2}$
(-10,-6)	0.0071 (1.15)	0.0008 (0.78)	0.0000 (0.00)	0.0001 (0.20)	0.0003 (0.06)	0.0000 (-0.05)	0.0003 (0.40)
(-5,-1)	0.0149** (2.43)	0.0024** (2.42)	0.0051 (0.84)	0.0012 (1.79)	0.0036 (0.73)	0.0007 (1.11)	0.0011 (1.64)
(-1,1)	0.0081 (1.70)	0.0021 (1.64)	0.0120** (2.54)	0.0022** (2.41)	0.0131*** (3.41)	0.0022*** (2.77)	0.0022*** (2.61)
(1,5)	-0.0076 (-1.23)	-0.0015 (-1.52)	-0.0085 (-1.39)	-0.0003 (-0.40)	-0.0037 (-0.75)	0.0002 (0.28)	-0.0001 (-0.21)
(6,10)	-0.0028 (-0.45)	-0.0004 (-0.44)	-0.0005 (-0.08)	-0.0005 (-0.69)	0.0012 (0.23)	-0.0003 (-0.49)	-0.0004 (-0.59)
(-2,2)	0.0037 (0.59)	0.0005 (0.53)	0.0039 (0.63)	0.0010 (1.40)	0.0052 (1.04)	0.0008 (1.36)	0.0008 (1.29)
(-3,3)	0.0035 (0.49)	0.0004 (0.50)	-0.0017 (-0.24)	0.0006 (0.93)	-0.0001 (-0.02)	0.0004 (0.71)	0.0004 (0.72)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS; $\hat{\beta}_{GLS\text{-}1}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for event/firm-specific heteroskedasticity; and $\hat{\beta}_{GLS\text{-}2}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both event/firm-specific heteroskedasticity and cross-sectional dependence arising from multi-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero.

*, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level (two-tailed test).