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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 mean abnormal returns. When arbitrage activity across these markets is restricted in some way, estimating abnormal returns from just one of the markets 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 develop a Generalized Least Squares estimator that (i) uses all the information available from multiple listings, (ii) 'downweights' listing observations that provide little new information, and (iii) yields efficient abnormal return estimates. Finally, we apply this generalized approach to a sample of Chinese foreign mergers and acquisitions and compare the results with conventional estimates of mean abnormal returns.

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, it has more recently been extended 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 mean abnormal returns. This question is potentially of great empirical importance: Approximately a third of all firms appearing in Datastream are 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] Based on authors' own calculations.. See also Karolyi (2006) for 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.

Although some 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]

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

[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.

different information sets. Hence, left to their own devices, they 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. They are incomplete because they ignore important information embedded in the price responses of other markets. In such circumstances, using returns from all those markets in which a 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, to the extent that price responses in different markets are not independent, simple pooling of multi-listed 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 describe a procedure that achieves these twin objectives and yields efficient estimates of abnormal returns. Moreover, by giving this procedure a straightforward Generalized Least Squares (GLS) interpretation, we are able to readily compare it with other estimators that have been commonly reported in the literature. Our approach is not entirely novel, having been largely anticipated by Collins and Dent (1984), but their focus is on cross-sectional correlations induced by industry concentration and hence they do not address the complications created by firm multiple-listings. Our contribution can, therefore, be thought of as an extension of their work to the latter, increasingly-important, phenomenon. We show that application of our procedure produces substantially different results than conventional estimates based upon average abnormal returns.

The rest of this paper proceeds as follows. Section 2 develops our generalized approach in steps, increasing the complexity of the error variance-covariance matrix associated with abnormal returns to arrive at a general case that incorporates the use of information from all firm-listings. Section 3 illustrates its use by applying it to a sample of foreign mergers and acquisitions by Chinese firms. Section 4 provides concluding remarks.

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

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

We begin by considering a sample of event data where either (i) firms are listed on a single stock exchange; or (ii) some firms are listed on multiple exchanges, but the researcher allows only one price reaction observation per event (i.e., multiple-listed shares are not allowed). To establish a benchmark, we impose the assumption that abnormal returns have homoskedastic and cross-sectionally independent errors. The remainder of this sub-section describes this simplified case

Let daily (adjusted) stock prices for each OMA firm-event i at time t be given by P_{it} , and let daily returns be computed as follows:

(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 firm-events in the sample, and t is measured relative to a given announcement day.[6] 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) is estimated for each firm-event i 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.

[6] We use the term "firm-event" to emphasize that a firm may engage in more than one event.

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 data generating process (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 daily abnormal returns; $\boldsymbol{\varepsilon}_t$ is an $N \times 1$ vector of error terms, $\boldsymbol{\varepsilon} \sim N(\boldsymbol{0}_N, \sigma^2 \boldsymbol{I}_N)$, $\boldsymbol{0}_N$ is an $N \times 1$ vector of zeroes, and $\boldsymbol{I}_N$ is the $N \times N$ identity matrix.

Given the assumptions above, the OLS estimate of β, $\hat{\beta}_{OLS}$, is efficient (Greene, 2011):

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

It is easily shown that

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

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

If σ^2 is known, then

(8) $$Var(AAR_t) = \sigma^2 \left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}$$, and

(9) $$s.e.(AAR_t) = \sqrt{\sigma^2 \left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}} .$$

The latter is equivalent to

(10) $$s.e.(AAR_t) = \frac{\sigma}{\sqrt{N}} .$$

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

(11) $$Z_{AAR} = \frac{AAR_t}{s.e.(AAR_t)} = \frac{\left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1} \boldsymbol{x}_t'\boldsymbol{y}_t}{\sqrt{\sigma^2 \left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1}}} ,$$

which can be written as

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

If σ^2 is unknown, we can estimate it by $\hat{\sigma}^2 = \dfrac{\sum_{s=1}^{S}\sum_{i=1}^{N}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{N(S-2)}$. Then $\hat{\sigma}$ replaces σ in the equations above, and critical *t*-values (instead of *Z*-values) are used for hypothesis testing.

The extension to multiple-day testing intervals is straightforward. Redefine the above such that

(13) $$\boldsymbol{y}_{T_1,T_2} = \boldsymbol{x}_{T_1,T_2}\beta + \boldsymbol{\varepsilon}_{T_1,T_2} ,$$

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

The OLS estimate of β is now

(14) $$\hat{\beta}_{OLS} = \left(\boldsymbol{x}'_{T_1,T_2}\boldsymbol{x}_{T_1,T_2}\right)^{-1}\boldsymbol{x}'_{T_1,T_2}\boldsymbol{y}_{T_1,T_2} = \frac{\sum_{i=1}^{N}\sum_{t=T_1}^{T_2} AR_{it}}{N(T_2 - T_1 + 1)} = AAR_{T_1,T_2},$$

where AAR_{T_1,T_2} is the average abnormal return over the interval (T_1,T_2) and over all N firms.

If σ^2 is known, the corresponding test statistic is given by

(15) $$Z_{AAR} = \frac{\left(\boldsymbol{x}'_{T_1,T_2}\boldsymbol{x}_{T_1,T_2}\right)^{-1}\boldsymbol{x}'_{T_1,T_2}\boldsymbol{y}_{T_1,T_2}}{\sqrt{\sigma^2\left(\boldsymbol{x}'_{T_1,T_2}\boldsymbol{x}_{T_1,T_2}\right)^{-1}}} = \frac{\sum_{t=T_1}^{T_2}\sum_{i=1}^{N}\left(AR_{it}/\sigma \right)}{\sqrt{N\left(T_2 - T_1 + 1\right)}}).$$

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

2.2 A Halfway Step: Single-Market Listing of Securities When Errors are Heteroskedastic but Cross-Sectionally Independent

We next consider the case where (i) error variances are heteroskedastic, while still assuming that (ii) abnormal returns are independent across observations. As we will show, this case provides an illustrative bridge towards a generalized estimator for multiple-listings, while also identifying relationships with test statistics that commonly appear in the literature.

It is common in event studies to assume that abnormal returns are heteroskedastic. There are many reasons for this. The nature of their respective input and output markets can cause firms' share prices to differ in volatility. In addition, when data are drawn from share markets in different countries, differences in exchange rate volatility, country risk and financial transparency can also contribute towards heteroskedastic errors.

Let the DGP again be given by

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

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. As is well-known, 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

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

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

(18) $$\tilde{\beta} = \left(\boldsymbol{x}_t'\boldsymbol{\Omega}^{-1}\boldsymbol{x}_t\right)^{-1}\boldsymbol{x}_t'\boldsymbol{\Omega}^{-1}\boldsymbol{y}_t,$$

and the estimated standard error is given by

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

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

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

and

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

In other words, $\tilde{\hat{\beta}}$ is identical to OLS applied to the 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,

(22) $$Z_{\tilde{\hat{\beta}}} = \frac{\tilde{\hat{\beta}}}{s.e.(\tilde{\hat{\beta}})} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}}.$$

A commonly used measure of average abnormal returns in the presence of heteroskedasticity is average standardized abnormal return (*ASAR*) (Strong, 1992; Atkas, N., E. de Bodt and J. Cousin, 2007),

(23) $$ASAR_t = \frac{\sum_{i=1}^{N}\left(AR_{it}/\sigma_i\right)}{N}.$$

The corresponding test statistic is

(24) $$Z_{ASAR} = \frac{\sum_{i=1}^{N}\left(AR_{it}/\sigma_i\right)}{\sqrt{N}}.$$

Interestingly, $Z_{ASAR} = \frac{\sum_{i=1}^{N}\left(AR_{it}/\sigma_i\right)}{\sqrt{N}}$ is not equal to $Z_{\tilde{\hat{\beta}}} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}}$.

We can see this by noting that

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

but

(26) $$Z_{\tilde{\hat{\beta}}} = \frac{(\tilde{x}_t'\tilde{x}_t)^{-1}\tilde{x}_t'\tilde{y}_t}{\sqrt{(\tilde{x}_t'\tilde{x}_t)^{-1}}}.$$

Z_{ASAR} and its multiple-period generalization 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 $Z_{ASAR} \neq Z_{\tilde{\hat{\beta}}}$ indicates that Z_{ASAR} is not the appropriate statistic for testing hypotheses about the mean of the distribution of abnormal returns, β (we discuss this further below).

If the σ_i , $i=1,2,\ldots,N$, are unknown, we replace them with their estimates $\hat{\sigma}_i = \frac{\sum_{s=1}^{S}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{S-2}$, $i = 1,2,\ldots N,$ 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 an estimate that varies across days within the test period to account for the fact that $\hat{R}_{it}$ in Equation (4) is a prediction.[7]

2.3 A Side Note: What Hypothesis Corresponds To Z_{ASAR}?

Given the widespread usage of Z_{ASAR_t}, we might ask what hypothesis corresponds to this test statistic. Consider the following regression:

(27) $$\tilde{y}_t = x_t\gamma + \varepsilon_t,$$

[7] 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).

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

The OLS estimator of γ is

(28) $$\hat{\gamma}_{OLS} = \left(\boldsymbol{x}_t'\boldsymbol{x}_t\right)^{-1} \boldsymbol{x}_t'\tilde{\boldsymbol{y}}_t = \frac{\sum_{i=1}^{N}\left({AR_{it}}/{\sigma_i} \right)}{N} = ASAR_t$$

and is efficient. The test statistic $Z_{ASAR} = \frac{\sum_{i=1}^{N}\left({AR_{it}}/{\sigma_i} \right)}{\sqrt{N}}$ corresponds to the null hypothesis that $\gamma = 0$.

In words, Z_{ASAR} is applicable for testing hypotheses about the mean of the distribution of *standardized* abnormal returns, γ; whereas $Z_{\tilde{\beta}}$ is applicable to tests about the mean of the distribution of *unstandardized* abnormal returns, β. There is no reason to expect $\gamma = \beta$, and it is the latter which is the usual object of interest.

2.4 The General Case: Multiple-Market Listing of Securities When Errors Are Heteroskedastic And Cross-Sectionally Correlated

We now consider the case where our sample consists of price reaction observations of the same event from multiple share markets. 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 treat them as independent observations and pool them.

We start off similarly to the heteroskedasticity case, allowing each of the *N* firm-event 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.

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

$$(29) \qquad \boldsymbol{y}_t = \begin{pmatrix} AR_{11t} \\ AR_{12t} \\ AR_{13t} \\ AR_{21t} \\ AR_{23t} \\ AR_{32t} \\ AR_{43t} \end{pmatrix}.$$

In this example, the first security is multiple-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.

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

$$(30) \qquad \boldsymbol{y}_t = \boldsymbol{x}_t\beta + \boldsymbol{\varepsilon}_t .$$

Define $\boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \sigma_N^2 \end{bmatrix}$, and $\boldsymbol{P}$ such that $\boldsymbol{P'P} = \boldsymbol{\Omega}^{-1}$. Pre-multiplying (30) by $\boldsymbol{P}$ gives $\boldsymbol{Py}_t = \boldsymbol{Px}_t\boldsymbol{\beta} + \boldsymbol{P\varepsilon}_t$, which can be rewritten as

$$(31) \qquad \tilde{\boldsymbol{y}}_t = \tilde{\boldsymbol{x}}_t\beta + \tilde{\boldsymbol{\varepsilon}}_t .$$

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

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

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 incorporate correlated abnormal returns for securities listed in more than one market. Let $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\boldsymbol{0}_N, \tilde{\boldsymbol{\Omega}})$, where

$$(33) \qquad \tilde{\boldsymbol{\Omega}} = \begin{bmatrix} 1 & \rho_{11,12} & \rho_{11,13} & 0 & 0 & 0 & 0 \\ \rho_{12,11} & 1 & \rho_{12,13} & 0 & 0 & 0 & 0 \\ \rho_{13,11} & \rho_{13,12} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \rho_{21,23} & 0 & 0 \\ 0 & 0 & 0 & \rho_{23,21} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

and $\rho_{ij,ik}$ refers to correlations of standardized abnormal returns between multiple-listed 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 corresponding GLS estimator of β is

$$(34) \qquad \hat{\beta}_{GLS} = \left(\tilde{\boldsymbol{x}}_t' \tilde{\boldsymbol{\Omega}}^{-1} \tilde{\boldsymbol{x}}_t\right)^{-1} \tilde{\boldsymbol{x}}_t' \tilde{\boldsymbol{\Omega}}^{-1} \tilde{\boldsymbol{y}}_t,$$

and

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

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

(36) $$Z_{\hat{\beta}_{GLS}} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}}.$$

If the σ_{ij} , $i=1,2,...,N$, are unknown, we substitute their estimated values, $\hat{\sigma}_{ij}$, $i=1,2,...,N$, 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 33). To achieve this, we follow a three-step process based on the "studentized" residual (as in "Student's" 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 variance. As a result, the standard deviation estimates, used to calculate the individual $AR_{ijs} / \hat{\sigma}_{ij}$ and $AR_{iks} / \hat{\sigma}_{ik}$ terms, will be time-varying during the estimation period (assuming the values of Rm_{js} change over time).

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

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

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. Define

(38) $$\hat{\varepsilon}_{ijs} \equiv AR_{ijs}\,.$$

Second, we estimate standard deviations for each of the $\hat{\varepsilon}_{ijs}$ so we can calculate individual standardized abnormal return values. To do that, we form the matrix, $\boldsymbol{X}_{ij}$:

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

We then calculate the "hat" matrix

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

The standard deviation of the s^{th} residual from the market model regression is estimated by

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

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 OLS estimation of Equation (37).

Third, we estimate the $\rho_{ij,ik}$. To do that, we take the standardized abnormal returns for the i^{th} firm in markets j and k at time s, $\frac{AR_{ijs}}{\hat{\sigma}_{ij}\sqrt{1-h_{ij}^{s}}}$ 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.[8] These respective estimates of $\rho_{ij,ik}$ are substituted into Equation (33), and $\hat{\beta}_{GLS}$ and $s.e.(\hat{\beta}_{GLS})$ are calculated accordingly (cf. Equations 34 and 35). Hypothesis testing proceeds in the usual fashion, with critical values for $Z_{\hat{\beta}_{GLS}}$ (cf. Equation 36) taken from the standard normal distribution because the underlying theory is asymptotic.

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

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

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

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

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

where $\tilde{\boldsymbol{y}}_{T_1,T_2}$ and $\tilde{\boldsymbol{x}}_{T_1,T_2}$ 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 $N(T_2 - T_1 + 1) \times N(T_2 - T_1 + 1)$.

The corresponding GLS estimator of β, the mean of the distribution of abnormal returns, is:

(45) $$\hat{\beta}_{GLS} = \left(\tilde{\boldsymbol{x}}'_{T_1,T_2}\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{x}}_{T_1,T_2}\right)^{-1}\tilde{\boldsymbol{x}}'_{T_1,T_2}\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{y}}_{T_1,T_2},$$

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

(46) $$s.e.\left(\hat{\beta}_{GLS}\right) = \sqrt{\left(\tilde{\boldsymbol{x}}'_{T_1,T_2}\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{x}}_{T_1,T_2}\right)^{-1}}.$$

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

(47) $$Z_{\hat{\beta}_{GLS}} = \frac{\left(\tilde{\boldsymbol{x}}'_{T_1,T_2}\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{x}}_{T_1,T_2}\right)^{-1}\tilde{\boldsymbol{x}}'_{T_1,T_2}\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{y}}_{T_1,T_2}}{\sqrt{\left(\tilde{\boldsymbol{x}}'_{T_1,T_2}\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{x}}_{T_1,T_2}\right)^{-1}}}.$$

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

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

Thus,

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

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

and,

(51) $$Z_{\hat{\beta}_{GLS}} = \frac{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}'_t\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}'_t\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t\right)}{\sqrt{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}'_t\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}} = \sqrt{\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}'_t\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t\right)^{-1}}\left(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}'_t\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t\right) .$$

To summarize, suppose a researcher has, for a given event type, price reaction data from firms listed in multiple markets. We expect the associated abnormal returns to be characterized by error terms that are both heteroskedastic and cross-sectionally correlated. As discussed earlier, pooling the listings without further adjustment would involve double-counting to the extent that multiple-listed observations contain common information. Instead, what is required is an appropriate weighting system that incorporates 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.

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 January 1, 1994 and December 31, 2009.[9] There are two reasons why this should be a useful application for assessing the potential contribution of our generalized methodology. First, the geographical

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

dispersion of OMAs means that information relevant to a particular event is likely to be dispersed across markets. For example, Chinese investors might be expected to have informational advantages concerning Chinese acquiring firms, while foreign investors may be better informed about overseas targets. Estimation of the total wealth effects emanating from OMAs requires aggregation of these individual-market/country information sets.

Second, Chinese firms that engage in OMAs list across multiple share markets. Prior literature (Chen et al., 2010; Gagnon & Karolyi, 2004) suggests that the China Mainland markets are not well integrated with other markets and that deviations from price parity are both common and substantial, something we confirm in the discussion below. Of course, the informational advantages from combining data across markets is inversely related to the degree the markets are integrated.

3.1 Summary Information on Multiple-listed Observations

To be included in our sample, the acquiring Chinese firm must have (i) its shares listed in at least one of the following exchanges: Shanghai and Shenzhen exchanges (China Mainland), SEHK (Hong Kong), NYSE, AMEX or NASDAQ (US); (ii) its stock price information available from DataStream; and (iii) 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 95 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.

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 Mainland, 30 in Hong Kong, and 31 in the US. The remaining 46 events are associated with dual-listed (36) or triple-listed (10) firms. In total, there are 213 firm-event observations in the sample when multiple-listings are taken into account. This compares with 66 firm-event observations if we restrict ourselves to events listed on home (China Mainland) markets. Of course, the full set of observations cannot 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 firm-event.

3.2. Summary Information for Correlations of Standardized Abnormal Returns

TABLE 2 summarizes the estimated correlations between standardized abnormal returns for the multiple-listed shares in our sample (see Section 2.4 for a discussion of how the respective $\rho_{ij,ik}$ terms are estimated). There are 10 pairwise correlations, $\rho_{ij,ik}$, for the China Mainland-US markets, 16 pairwise correlations for the China Mainland-Hong Kong markets, and 40 for the Hong Kong-US markets. These pairwise correlations are calculated over the estimation periods corresponding to the respective events.

The table reports much lower correlations for abnormal returns associated with shares jointly listed on the China Mainland and overseas markets, compared to shares jointly listed in the Hong Kong and US markets. The mean value of pairwise correlations for the China Mainland–US and China Mainland–Hong Kong markets are 0.121 and 0.090, respectively; compared to 0.622 for the Hong Kong–US markets.[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 the China Mainland exchanges are not exchangeable with shares of the same firm listed in Hong Kong. Further, Chinese citizens are prohibited from investing in Hong Kong. These

[10] Empirical studies show that correlation between different markets are relatively 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).

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. Consistent with that, the Hong Kong–US, dual-listed pairs have relatively high correlations, despite significant differences in market closing times as a result of being in different time zones.

Further insight on the relationship between dual-listed share prices is given by TABLE 3.[12] This table reports mean absolute percentage deviations (MAPDs) in closing prices for all shares that are multiple-listed. We report one MAPD value for each firm, calculating price disparities for multiple-listed firms as they existed during calendar year 2008. These will differ from price deviations that existed during the respective estimation windows. However, the MAPD values reported in TABLE 3 should be sufficient to yield insights into the correlations reported in TABLE 2.

As noted above, shares are exchangeable between the Hong Kong and US markets. We therefore expect price deviations to be very small, and due entirely to different closing times across the two markets. The first row of TABLE 3 reports mean, median, minimum, and maximum MAPD values for the 12 firms in our full sample that list on both the Hong Kong and U.S. share markets. The average price deviation is 1.1 percent. The minimum and maximum deviations are 1 and 2 percent, respectively.

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[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.

[12] Share price data are taken from calendar year 2008.

In contrast, price disparities are much greater between the China Mainland–Hong Kong and China Mainland–US markets (cf. Columns 2 and 3). The average MAPD is 16.3 percent for shares that are listed on the China Mainland – Hong Kong markets, and 11.8 percent for shares listed on the China Mainland - US markets.[13] These results are consistent with the existence of barriers to exchangeability, as noted above.

Together, TABLES 2 and 3 document that the multiple-listed shares in our dataset are imperfectly correlated, with the degree of correlation being dependent on the specific markets where they are listed. They provide evidence that different markets contain independent information.

3.3. Comparison of AAR and GLS Estimators

Once we are convinced that multiple-listings provide useful information, it follows that event-study methodology should appropriately aggregate that information. The GLS estimator provides two benefits. First, it allows us to obtain efficient estimates of the mean of the distribution of daily abnormal returns. Second, because it enables the use of multiple-listings, it allows the researcher to use more observations than would be appropriate when calculating conventional average abnormal returns (=OLS). In this section, we demonstrate the applicability of the GLS estimator, while identifying the practical difference its use can make.

TABLE 4 reports estimates of the mean of the distribution of daily abnormal returns, β, over various intervals.[14] The first two columns report estimates when using the "Home" (=China Mainland) and "Highest Volume" markets. The estimates are calculated using OLS (=AAR). A comparison of these two columns illustrates the effect of expanding the number

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[13] We employ US dollar prices and all the time series prices in year 2008 are from DataStream. The formula for Mean Absolute Percentage Deviation (MAPD) is: $P_{MAPD} = \dfrac{|p_1 - p_2|}{(p_1 + p_2)/2}$.

[14] While we have not subscripted β by time, we expect the population mean of the distribution of abnormal returns to change according to proximity to the announcement day if the OMA is expected to affect shareholder wealth.

of observations and including information from different markets, holding the estimation procedure constant. The last column reports GLS estimates based on all observations, including multiple-listed shares. The results in this column combine the effects of (i) expanding the number of observations with (ii) using a different (efficient) estimator of β.

Columns (1) and (2) both only allow one listing per firm-event. The difference is that the Highest Volume sample of Column (2) includes observations from all three sets of markets. Previous tables indicated that different markets provide independent information about the same event. Accordingly, we would expect that including observations from markets outside the China Mainland would produce different estimates of β – and they do. For example, the Home sample finds a significant, mean daily abnormal return on the (-5,-1) window. In contrast, the Highest Volume sample finds a significant, mean daily AR on the (-1,1) window.

Column (3) reports the results of expanding the sample to include all observations, including all occurrences of multiple-listed shares; and using GLS procedure to estimate β. Compared to the Highest Volume sample, the (-1,1) window is still the only significant interval. However, the GLS estimate is substantially smaller than AAR (=OLS) for the same interval. GLS produces a mean daily AR estimate of 0.22 percent over the (-1,1) window, compared to an average abnormal return value of 1.20 percent using the Highest Volume sample.

TABLE 5 parses abnormal returns over the individual days of the 21-day testing window. As before, the first two columns compare OLS estimates of β across the Home and Highest Volume samples, while the third column reports GLS estimates of β using all listings. Estimates using the Home market sample find significant ARs on Days -1 and 2. The Highest Volume sample produces significant ARs on Day -5, Day 2, and Day 3. And the All Listings sample yields a lone, significant AR on Day -1. The latter result is consistent with the interval results reported in TABLE 4. The AAR results for the other two samples are not consistent with TABLE 4.

TABLES 4 and 5 demonstrate that GLS can produce substantially different estimates than conventional average abnormal returns. For example, the OLS(=AAR) estimates of TABLE 5 provide evidence of a negative and significant reversal after an initial, positive announcement effect: Abnormal returns on Day 2 are negative and significant for both the Home and Highest Volume samples, and negative and significant on Day 3 for the Highest Volume sample. In contrast, the GLS results show no significant evidence of a post-announcement reversal.

There are two reasons that the GLS procedure we develop here can be expected to produce different results than conventional estimates. First, GLS allows a larger sample to be employed because multiple-listings of the same share can be included. This allows not just more, but potentially different information to be included. For example, in the case of OMAs where information about the quality of a match may be geographically dispersed across different markets, this additional information allows a more accurate assessment of the expected effect of the event on shareholders of the acquiring firm. A second reason that GLS is expected to produce different results is that it makes efficient use of the information in the larger sample. Conventional methods, such as average abnormal returns, are inefficient. Both factors play a role in generating the different estimates.[15]

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

[15] TABLES A.3 and A.4 in the Appendix report the results of TABLES 3 and 4, respectively, but add an additional column that allows one to identify how much of the differences between the Highest Volume and All listings is attributed to larger sample size, and how much is due to using a different estimation procedure. A comparison of Column (2) with Columns (3) and (4) in these tables make it clear that both factors play a role.

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 a generalized least squares (GLS) procedure that efficiently incorporates the relationship of share price performance across multiple exchanges.

Our theoretical development of the GLS procedure also allows a direct comparison with 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 *standardized* 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 mean 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 datasets – Home (=China Mainland) listings, Highest Volume listings, and All listings. We demonstrate that our GLS procedure produces substantially different results than conventional average abnormal returns (AAR). This is because our approach (i) allows the use of more observations, and (ii) efficiently aggregates the information from those observations.

As noted above, approximately a third of the firms appearing in Datastream are listed in at least two markets. Accordingly, the approach developed in this paper may be useful in a wide variety of event studies because it allows researchers to exploit the additional information available from these multiple-listed observations.

Finally, while it is true that GLS produces efficient estimates, it is well-known that the associated standard error estimates can be understated, sometimes severely. For example, within a panel data framework, Reed and Ye (2011) find substantial efficiency improvements over OLS in the presence of cross-sectional correlation, but find that coverage rates are adversely affected by the number of non-zero parameters in the error variance-covariance matrix. The error variance-covariance matrices of Equations (33) and (48) display far fewer non-zero parameters than the troublesome cases considered by Reed and Ye (2011). Nevertheless, further study of the reliability of standard error estimation in the context of cross-sectional correlation from multiple-listings is called for. This is a topic for future research.

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TABLE 1
SUMMARY INFORMATION ON MULTIPLE-LISTED OBSERVATIONS

LISTING	***NUMBER OF FIRMS***	***NUMBER OF EVENTS***	***NUMBER OF OBSERVATIONS***
China Mainland only	40	50	50
Hong Kong only	22	30	30
U.S. only	17	31	31
China Mainland and Hong Kong	4	6	12
China Mainland and U.S.	0	0	0
Hong Kong and U.S.	8	30	60
China Mainland, Hong Kong and U.S.	4	10	30
TOTAL	95	157	213

TABLE 2
SUMMARY INFORMATION FOR CORRELATIONS OF STANDARDIZED ABNORMAL RETURNS FOR MULTIPLE-LISTED SHARES

MARKETS	*NUMBER OF CORRELATION TERMS*	*MEAN*	*MEDIAN*	*MIN*	*MAX*
$\rho_{ij,ik}$: ***i = China Mainland*** ***j = US***	10	0.121	0.101	-0.081	0.493
$\rho_{ij,ik}$: ***i = China Mainland*** ***j = Hong Kong***	16	0.090	0.092	-0.173	0.376
$\rho_{ij,ik}$: ***i = Hong Kong*** ***j = US***	40	0.622	0.636	0.375	0.904

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 (33) in the text.

TABLE 3

PRICE DEVIATIONS FOR SHARES LISTED ON MULTIPLE MARKETS (MEAN ABSOLUTE PERCENTAGE DEVIATION)

MARKETS	***NUMBER OF FIRMS***	***MEAN***	***MEDIAN***	***MIN***	***MAX***
HONG KONG – US[1]	12	0.011	0.010	0.010	0.020
CHINA MAINLAND – HONG KONG	8	0.163	0.140	0.030	0.480
CHINA MAINLAND - US	4	0.118	0.140	0.030	0.160

[1] Price deviation summary does not include data for Yuexiu Property. See TABLE A.2 for an explanation.

NOTE: Mean Absolute Percentage Deviation (*MAPD*) between prices p_1 and p_2 is calculated as $MAPD = \frac{|p_1 - p_2|}{(p_1 + p_2)/2}$. All prices are first converted to US dollars. Price series are taken from year 2008 in DataStream.

TABLE 4
COMPARISON OF ESTIMATES OF MEAN DAILY ARs USING DIFFERENT SAMPLES AND ESTIMATORS: INTERVALS

INTERVAL	***HOME (66 Obs)*** $\hat{\beta}_{OLS} = AAR$ ***(1)***	***HIGHEST VOLUME (157 Obs)*** $\hat{\beta}_{OLS} = AAR$ ***(2)***	***ALL LISTINGS (213 Obs)*** $\hat{\beta}_{GLS}$ ***(3)***
(-10,-6)	0.0071 (1.15)	0.0000 (0.00)	0.0003 (0.40)
(-5,-1)	0.0149** (2.43)	0.0051 (0.84)	0.0011 (1.64)
(-1,1)	0.0081 (1.70)	0.0120** (2.54)	0.0022*** (2.61)
(1,5)	-0.0076 (-1.23)	-0.0085 (-1.39)	-0.0001 (-0.21)
(6,10)	-0.0028 (-0.45)	-0.0005 (-0.08)	-0.0004 (-0.59)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS. It is equivalent to average abnormal return (AAR). $\hat{\beta}_{GLS}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both firm-event-specific heteroskedasticity, and cross-sectional dependence arising from multiple-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero. The GLS procedure adjusts standard errors for prediction errors according to Footnote 7.

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

TABLE 5

COMPARISON OF ESTIMATES OF MEAN DAILY ARs USING DIFFERENT SAMPLES AND ESTIMATORS: DAYS

DAY	***HOME (66 Obs)*** $\hat{\beta}_{OLS} = AAR$ ***(1)***	***HIGHEST VOLUME (157 Obs)*** $\hat{\beta}_{OLS} = AAR$ ***(2)***	***ALL LISTINGS (213 Obs)*** $\hat{\beta}_{GLS}$ ***(4)***
-10	0.0011 (0.38)	0.0026 (0.94)	0.0022 (1.53)
-9	0.0037 (1.35)	0.0025 (0.92)	0.0023 (1.59)
-8	0.0018 (0.64)	-0.0003 (-0.10)	-0.0005 (-0.34)
-7	0.0001 (0.02)	-0.0031 (-1.15)	-0.0001 (-0.08)
-6	0.0005 (0.17)	-0.0017 (-0.61)	-0.0026 (-1.81)
-5	0.0040 (1.45)	0.0061** (2.22)	0.0009 (0.66)
-4	0.0009 (0.32)	-0.0023 (-0.85)	0.0016 (1.12)
-3	-0.0003 (-0.10)	0.0000 (0.00)	0.0010 (0.66)
-2	0.0016 (0.59)	-0.0022 (-0.81)	-0.0012 (-0.80)
-1	0.0087*** (3.18)	0.0036 (1.32)	0.0029** (2.01)
0	0.0003 (0.11)	0.0044 (1.61)	0.0011 (0.77)
1	-0.0010 (-0.35)	0.0040 (1.48)	0.0025 (1.72)
2	-0.0060** (-2.20)	-0.0059** (-2.17)	-0.0012 (-0.82)

DAY	***HOME (66 Obs)*** $\hat{\beta}_{OLS} = AAR$ ***(1)***	***HIGHEST VOLUME (157 Obs)*** $\hat{\beta}_{OLS} = AAR$ ***(2)***	***ALL LISTINGS (213 Obs)*** $\hat{\beta}_{GLS}$ ***(4)***
3	0.0002 (0.068)	-0.0056** (-2.05)	-0.0024 (-1.65)
4	-0.0045 (-1.64)	-0.0024 (-0.86)	-0.0011 (-0.78)
5	0.0038 (1.37)	0.0014 (0.50)	0.0015 (1.061)
6	-0.0010 (-0.36)	-0.0017 (-0.63)	-0.0012 (-0.82)
7	0.0029 (1.06)	0.0045 (1.65)	0.0010 (0.69)
8	0.0010 (0.38)	0.0005 (0.18)	0.0009 (0.62)
9	-0.0023 (-0.85)	-0.0006 (-0.23)	-0.0011 (-0.80)
10	-0.0034 (-1.24)	-0.0031 (-1.13)	-0.0014 (-1.00)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS. It is equivalent to average abnormal return (AAR). $\hat{\beta}_{GLS}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both firm-event-specific heteroskedasticity, and cross-sectional dependence arising from multiple-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero. The GLS procedure adjusts standard errors for prediction errors according to Footnote 7.

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

APPENDIX
TABLE A.1
INDIVIDUAL CORRELATIONS UNDERLYING TABLE 2

CHINA MAINLAND – US ***(1)***		***CHINA MAINLAND – HONG KONG*** ***(2)***		***HONG KONG - US*** ***(3)***	
China Life Insurance	0.045	Aluminum Corp.of China	0.106	China Life Insurance Co Ltd	0.413
PetroChina	0.089	Anshan Iron & Steel Group Corp	0.101	China Mobile	0.407
Sinopec	-0.066	China Life Insurance Co Ltd	0.197	China Mobile	0.431
Sinopec	0.113	China Nonferrous Metal Ind	-0.173	China Mobile	0.534
Sinopec	0.157	China Nonferrous Metal Ind	-0.073	China Mobile	0.493
Sinopec	0.189	Huaneng Power Intl Inc	0.030	China Netcom Grp(HK)Corp Ltd	0.776
Sinopec	0.493	Huaneng Power Intl Inc	0.046	China Resources Entrp Ltd	0.703
Yanzhou Coal Mining	-0.081	PetroChina	0.375	China Resources Entrp Ltd	0.779
Yanzhou Coal Mining	-0.004	Sinopec	-0.097	China Telecom Corp Ltd	0.721
Yanzhou Coal Mining	0.277	Sinopec	0.040	China Unicom Ltd	0.556
		Sinopec	0.152	China Unicom Ltd	0.609
		Sinopec	0.159	CNOOC Ltd	0.476
		Sinopec	0.376	CNOOC Ltd	0.57
		Yanzhou Coal Mining Co Ltd	-0.123	CNOOC Ltd	0.648
		Yanzhou Coal Mining Co Ltd	0.083	CNOOC Ltd	0.71
		Yanzhou Coal Mining Co Ltd	0.237	CNOOC Ltd	0.727
				CNOOC Ltd	0.734
				CNOOC Ltd	0.743
				Guangzhou Investment Co Ltd[1]	0.904
				Lenovo Group Ltd	0.68

CHINA MAINLAND – US (1)		*CHINA MAINLAND – HONG KONG* (2)		*HONG KONG - US* (3)	
				Lenovo Group Ltd	0.795
				Lenovo Group Ltd	0.821
				PetroChina	0.375
				PetroChina	0.376
				PetroChina	0.396
				PetroChina	0.506
				PetroChina	0.548
				PetroChina	0.621
				PetroChina	0.633
				PetroChina	0.649
				PetroChina	0.693
				PetroChina	0.755
				Sinopec	0.524
				Sinopec	0.566
				Sinopec	0.637
				Sinopec	0.663
				Sinopec	0.672
				Yanzhou Coal Mining Co Ltd	0.623
				Yanzhou Coal Mining Co Ltd	0.635
				Yanzhou Coal Mining Co Ltd	0.777

[1] Guangzhou Investment Co Ltd later changed its name to Yuexiu Property.

NOTE: Correlations in table represent sample correlation coefficients for each firm-event during the respective estimation period.

APPENDIX
TABLE A.2
INDIVIDUAL PRICE DEVIATION DATA UNDERLYING TABLE 3

CHINA MAINLAND – US (1)		***CHINA MAINLAND – HONG KONG (2)***		***HONG KONG - US (3)***	
China Life Insurance	0.03	Aluminum Corp.Of China	0.17	China Life Insurance	0.01
PetroChina	0.16	Angang Steel	0.05	China Mobile	0.01
Sinopec	0.15	China Life Insurance	0.03	China Netcom Gp.Corp.	0.01
Yanzhou Coal Mining	0.13	China Nonferrous Mtl.	0.48	China Res.Enterprise	0.02
		Huaneng Power Intl.	0.13	China Telecom	0.01
		PetroChina	0.16	China Unicom	0.01
		Sinopec	0.15	CNOOC	0.01
		Yanzhou Coal Mining	0.13	Lenovo Group	0.01
				PetroChina	0.01
				Sinopec	0.01
				Yanzhou Coal Mining	0.01
				Yuexiu Property[1]	0.14

[1] Yuexui Property was previously known as Guangzhou Investment Co Ltd. The price deviation data for Yuexui Property is an aberration due to its thin trading. It was only traded twice during 2008. Whenever it was traded, the price deviation was eliminated. It was therefore not included in the summary data of TABLE 3. Note that it was much more actively traded during the estimation period, as it satisfied the requirement of being traded on at least half of the 126 days during the estimation period.

NOTE: Number in table report Mean Absolute Percentage Deviation (*MAPD*) and are calculated as $MAPD = \frac{|p_1 - p_2|}{(p_1 + p_2)/2}$. All prices are first converted to US dollars. Price series are taken from calendar year 2008 in DataStream.

APPENDIX

TABLE A.3

COMPARISON OF ESTIMATES OF MEAN DAILY ARs USING DIFFERENT SAMPLES AND ESTIMATORS: INTERVALS

INTERVAL	*HOME (66 Obs)*	*HIGHEST VOLUME (157 Obs)*	*ALL LISTINGS (213 Obs)*	
	$\hat{\beta}_{OLS}$ = *AAR* *(1)*	$\hat{\beta}_{OLS}$ = *AAR* *(2)*	$\hat{\beta}_{OLS}$ = *AAR* *(3)*	$\hat{\beta}_{GLS}$ *(4)*
(-10,-6)	0.0071 (1.15)	0.0000 (0.00)	0.0003 (0.06)	0.0003 (0.40)
(-5,-1)	0.0149** (2.43)	0.0051 (0.84)	0.0036 (0.73)	0.0011 (1.64)
(-1,1)	0.0081 (1.70)	0.0120** (2.54)	0.0131*** (3.41)	0.0022*** (2.61)
(1,5)	-0.0076 (-1.23)	-0.0085 (-1.39)	-0.0037 (-0.75)	-0.0001 (-0.21)
(6,10)	-0.0028 (-0.45)	-0.0005 (-0.08)	0.0012 (0.23)	-0.0004 (-0.59)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS. It is equivalent to average abnormal return (AAR). $\hat{\beta}_{GLS}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both firm-event-specific heteroskedasticity, and cross-sectional dependence arising from multiple-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero. The GLS procedure adjusts standard errors for prediction errors according to Footnote 7. This is the same table as TABLE 4, except that it also includes the OLS estimates of β using the multiple-listing sample of 213 observations.

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

APPENDIX

TABLE A.4

COMPARISON OF ESTIMATES OF MEAN DAILY ARs USING DIFFERENT SAMPLES AND ESTIMATORS: DAYS

DAY	***HOME (66 Obs)***	***HIGHEST VOLUME (157 Obs)***	***ALL LISTINGS (213 Obs)***	
	$\hat{\beta}_{OLS} = AAR$ ***(1)***	$\hat{\beta}_{OLS} = AAR$ ***(2)***	$\hat{\beta}_{OLS} = AAR$ ***(3)***	$\hat{\beta}_{GLS}$ ***(4)***
-10	0.0011 (0.38)	0.0026 (0.94)	0.0026 (1.19)	0.0022 (1.53)
-9	0.0037 (1.35)	0.0025 (0.92)	0.0026 (1.15)	0.0023 (1.59)
-8	0.0018 (0.64)	-0.0003 (-0.10)	-0.0004 (-0.18)	-0.0005 (-0.34)
-7	0.0001 (0.02)	-0.0031 (-1.15)	-0.0033 (-1.47)	-0.0001 (-0.08)
-6	0.0005 (0.17)	-0.0017 (-0.61)	-0.0012 (-0.54)	-0.0026 (-1.81)
-5	0.0040 (1.45)	0.0061** (2.22)	0.0051** (2.27)	0.0009 (0.66)
-4	0.0009 (0.32)	-0.0023 (-0.85)	-0.0015 (-0.65)	0.0016 (1.12)
-3	-0.0003 (-0.10)	0.0000 (0.00)	-0.0005 (-0.24)	0.0010 (0.66)
-2	0.0016 (0.59)	-0.0022 (-0.81)	-0.0028 (-1.24)	-0.0012 (-0.80)
-1	0.0087*** (3.18)	0.0036 (1.32)	0.0033 (1.49)	0.0029** (2.01)
0	0.0003 (0.11)	0.0044 (1.61)	0.0044** (1.98)	0.0011 (0.77)
1	-0.0010 (-0.35)	0.0040 (1.48)	0.0054** (2.43)	0.0025 (1.72)

DAY	HOME (66 Obs)	HIGHEST VOLUME (157 Obs)	ALL LISTINGS (213 Obs)	
	$\hat{\beta}_{OLS}$ = AAR (1)	$\hat{\beta}_{OLS}$ = AAR (2)	$\hat{\beta}_{OLS}$ = AAR (3)	$\hat{\beta}_{GLS}$ (4)
2	-0.0060** (-2.20)	-0.0059** (-2.17)	-0.0052** (-2.34)	-0.0012 (-0.82)
3	0.0002 (0.068)	-0.0056** (-2.05)	-0.0047** (-2.13)	-0.0024 (-1.65)
4	-0.0045 (-1.64)	-0.0024 (-0.86)	-0.0010 (-0.45)	-0.0011 (-0.78)
5	0.0038 (1.37)	0.0014 (0.50)	0.0018 (0.83)	0.0015 (1.061)
6	-0.0010 (-0.36)	-0.0017 (-0.63)	0.0000 (-0.01)	-0.0012 (-0.82)
7	0.0029 (1.06)	0.0045 (1.65)	0.0034 (1.53)	0.0010 (0.69)
8	0.0010 (0.38)	0.0005 (0.18)	0.0010 (0.43)	0.0009 (0.62)
9	-0.0023 (-0.85)	-0.0006 (-0.23)	-0.0004 (-0.19)	-0.0011 (-0.80)
10	-0.0034 (-1.24)	-0.0031 (-1.13)	-0.0028 (-1.25)	-0.0014 (-1.00)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS. It is equivalent to average abnormal return (AAR). $\hat{\beta}_{GLS}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both firm-event-specific heteroskedasticity, and cross-sectional dependence arising from multiple-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero. The GLS procedure adjusts standard errors for prediction errors according to Footnote 7. This is the same table as TABLE 4, except that it also includes the OLS estimates of β using the multiple-listing sample of 213 observations.

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