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INFORMATION ASYMMETRY, MARKET SEGMENTATION AND CROSS-LISTING: IMPLICATIONS FOR EVENT STUDY METHODOLOGY

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Abstract

This paper connects three subjects related to international financial markets -- (i) information asymmetry, (ii) market segmentation, and (iii) cross-listings -- and highlights their implication for event study methodology. When firms list equities on more than one exchange, and the exchanges are characterized by different information sets, a problem arises as to which exchange(s) to include in the event study sample. If market segmentation impedes the arbitrage of these multiple responses, then the use of a single listing (for a firm that is cross-listed) can yield abnormal return estimates that are biased. In such circumstances, using returns from all the 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. 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 develop an estimation procedure that achieves these twin objectives. We then apply our approach to an event study of Chinese OMAs and compare results from alternative samples and estimators. We demonstrate that including return data from cross-listings of the same firm can result in substantially different conclusions.

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

JEL Classifications: C12, G14, G15, G34

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INFORMATION ASYMMETRY, MARKET SEGMENTATION, AND CROSS-LISTING: IMPLICATIONS FOR EVENT STUDY METHODOLOGY

1. INTRODUCTION.

This paper connects three subjects related to international financial markets – (i) information asymmetry, (ii) market segmentation, and (iii) cross-listings – and highlights their implication for event study methodology. When firms list equities on more than one exchange, and the exchanges are characterized by different information sets and market segmentation, a problem arises as to which exchange(s) to include in the event study sample. This issue, and its implications, have not been fully appreciated in the literature.

There are many event studies that analyze return data from firms that list on multiple markets. These have used a variety of approaches in constructing their samples. The most common is to use returns from the firm's home market, e.g., Kim (2003); Aktas, de Bodt and Roll (2004); Doidge (2004); Bailey, Karolyi and Salva (2006); Faccio, McConnell and Stolin (2006); and Wang and Boateng (2007). Others, such as Aybar and Ficici (2009) and Campbell, Cowan and Salotti (2010), use returns from the firm's 'primary' (highest volume) market.[1] A third approach focuses on market returns from the U.S. (Chan, Cheung and Wong; 2002). Many studies provide little indication of how they proceed in this area (Amihud, DeLong and Saunders, 2002; Beitel, Schiereck and Wahrenburg, 2004; Anand, Capron and Mitchell, 2005; Keloharju, Knüpfer and Torstila, 2008; Ma, Pagán and Chu, 2009; and Ekkayokkaya, Holmes and Paudyal, 2009). A final option – pooling cross-listed observations from different markets – has, to the best of our knowledge, never been used. None of the papers referenced above discusses alternative approaches, nor offers a rationale in favor of the approach they adopt. None compares results from different approaches.

The use of different approaches in event studies would likely not be much of a concern if information asymmetry and market segmentation were not significant features of international financial markets. However, there exists substantial evidence that they are, at least for emerging markets.

[1] Campbell, Cowan and Salotti (2010 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.

The evidence for informational asymmetry in international share markets is extensive, and comes from a variety of sources: studies of (i) Chinese A and B shares (Chakravarty, Sarkar, and Wu, 1998); (ii) trading of non-US stocks by NYSE specialists (Bacidore and Sofianos, 2002; Phylaktis and Korczak, 2005); (iii) determinants of “home bias” in investment portfolios (Ahearne, Griever, and Warnock, 2004), (iv) analyses of cross-listings (Stulz, 1999; Lang, Lins, and Miller; 2003; Karolyi, 2006; Gagnon and Karolyi, 2009); (v) informational advantages of foreign versus domestic traders (Chan, Menkveld, and Yang, 2007); and (vi) market leadership in price discovery (Eun and Sabherwal, 2003; Grammig, Melvin, and Schlag, 2004; Pascual, Pascual-Fuster and Climent, 2006).

Information asymmetry, by itself, would not be a great concern if traders quickly arbitraged differences in information sets across markets. However, many studies, using a variety of approaches, report evidence of market segmentation, especially for emerging markets. De Jong and de Roon (2005) analyze stock returns from 30 emerging markets over the period 1988-2000. While they find that markets have become increasingly integrated over time, many emerging markets continue to experience substantial market segmentation, particularly in Asia and the Far East. Carrieri, Errunza, and Hogan (2007) study eight emerging markets over the period 1977-2000 and conclude that “mild segmentation is a reasonable characterization for emerging markets (page 917).” Chambet and Gibson (2008) study share markets in 25 emerging markets from 1995 to 2004 and conclude that “emerging markets still remain to a large extent segmented and that financial integration has decreased during the financial crises of the 1990s (page 654).” And Bekaert, Harvey, Lundblad, and Siegel (2011) in their extensive analysis of markets from 69 countries from 1980 to 2005 conclude, “While we observe decreased levels of segmentation in many countries, the level of segmentation remains significant in emerging markets (page 3841).”

Cross-listing of shares in foreign markets has become a relatively common phenomenon. Karolyi (2006) reports that U.S. holdings of foreign equities accounted for approximately 12% of the asset base of U.S. investors in 2003. Emerging markets have become an increasingly important source of foreign listings on U.S. markets. Data for foreign listings on non-U.S. markets are more difficult to come by, but Karolyi estimates that foreign listings account for approximately 10% of total listings on non-U.S., major exchanges. Our own calculations find that approximately a third of all firms appearing in Datastream are listed in at least two markets. Thus, event studies that analyse price responses from firms located in emerging countries are likely to discover that a substantial proportion of their firms list on multiple markets.

For reasons discussed above, investors in different markets may possess different information sets. Accordingly, they may respond differently to a given event. This is especially true when the event being analyzed has both domestic and foreign dimensions. For example, in the case of overseas mergers and acquisitions (OMAs), domestic traders may be more knowledgeable about the acquirer, and foreign investors more knowledgeable about the target.[2]

If market segmentation impedes the arbitrage of these multiple responses, then the use of a single listing (for a firm that is cross-listed) can yield abnormal return estimates that are biased. The bias stems from the fact that the estimates ignore important information embedded in the price responses of other markets. Further, the bias may be difficult to sign *a priori* because it depends on the specific nature of the differences in the non-overlapping components of the respective iinformation sets. In such circumstances, using returns from all the 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 develop an estimation procedure that achieves these twin objectives. We then apply our approach to an event study of Chinese OMAs and compare results from alternative samples and estimators. We demonstrate that including return data from multiple listings of the same firm can result in substantially different conclusions.

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.

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[2] Wang and Xie (2009) find that acquisitions of firms with poor corporate governance by firms with good corporate governance generate positive prices responses from markets. While their study focussed on shareholder rights, the argument would seem to extend to other differences in characteristics between firms. Market traders in a firm's home environment may be more familiar with the acquirer, while traders in foreign markets may be more familiar with the target. Hence, to include the price responses from one, while omitting the price responses of the other, biases the overall market evaluation of the firm.

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 are homoskedastic and cross-sectionally independent. 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.[3] 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.

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),

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

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

In this benchmark case, 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) $Var(AAR_t) = \sigma^2 (\boldsymbol{x}_t' \boldsymbol{x}_t)^{-1}$, and

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

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

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 $\hat{\sigma}^2 = \frac{\sum_{s=1}^{S}\sum_{i=1}^{N}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{N(S-2)}$. 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 $N(T_2\text{-}T_1+1)\times 1$ 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 $N(T_2\text{-}T_1+1)\times 1$ 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 $N(T_2\text{-}T_1+1)\times 1$ 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 $N(T_2\text{-}T_1+1)\times 1$ vector of zeroes, and $\boldsymbol{I}_{N(T_2-T_1+1)}$ is the identity matrix of order $N(T_2\text{-}T_1+1)$.

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, $\boldsymbol{\varepsilon}_t \sim N\left(\boldsymbol{0}_N, \boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_N^2 \end{bmatrix}\right)$, 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) $$\boldsymbol{P} = \boldsymbol{P}' = \begin{bmatrix} \frac{1}{\sigma_1} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sigma_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \frac{1}{\sigma_N} \end{bmatrix}.$$

Assuming the $\sigma_i^{\,2}$, i=1,2,…,N are known, the GLS estimator of β given this first generalization is given by

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

and the standard error is given by

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

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

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

and

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

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

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

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

This is seen from the fact that

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

but

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

Z_{ASAR} 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 – without further assumptions – 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,…,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 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.[4]

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[4] 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).

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

where $\tilde{\boldsymbol{y}}_t$ is an $N \times 1$ vector of standardized abnormal returns, $\left(\frac{AR_{it}}{\sigma_i} \right)$, $i = 1,2,...,N$; $\boldsymbol{x}_t$ 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, $\boldsymbol{\varepsilon}_t \sim N(\boldsymbol{0_N}, \boldsymbol{I_N})$.

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 naively 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 $\boldsymbol{\Omega} = \begin{bmatrix} \sigma_{11}^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{12}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{13}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{21}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{23}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{32}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{43}^2 \end{bmatrix}$, and $\boldsymbol{P}$ such that $\boldsymbol{P'P} = \boldsymbol{\Omega}^{-1}$. Pre-multiplying (30) by $\boldsymbol{P}$ gives $\boldsymbol{P}\boldsymbol{y}_t = \boldsymbol{P}\boldsymbol{x}_t\boldsymbol{\beta} + \boldsymbol{P}\boldsymbol{\varepsilon}_t$, 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

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

and

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

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*, $\dfrac{AR_{ijs}}{\hat{\sigma}_{ij}\sqrt{1-h_{ij}^{s}}}$ and $\dfrac{AR_{iks}}{\hat{\sigma}_{ik}\sqrt{1-h_{ik}^{s}}}$, $s=1,2,\ldots,S$, and calculate the associated sample correlation between the two series.[5] These respective estimates of $\rho_{ij,ik}$ are substituted into Equation (33), and $\hat{\beta}_{GLS}$ and $s.e.\left(\hat{\beta}_{GLS}\right)$ 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) $$\tilde{\boldsymbol{y}}_{T_1,T_2} = \begin{bmatrix} \tilde{\boldsymbol{y}}_{T_1} \\ \tilde{\boldsymbol{y}}_{T_1+1} \\ \vdots \\ \tilde{\boldsymbol{y}}_{T_2} \end{bmatrix},$$

(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 $N(T_2 - T_1 + 1)\times N(T_2 - T_1 + 1)$.

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

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

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

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

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

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

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

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

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

Thus,

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

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

and,

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

A further advantage of this formulation is that the analysis is easily extended to include explanatory variables.

2.5. Advantages and Disadvantages of the Generalized Event Study Method with Cross-listings.

The main advantage of the generalized approach above is that it allows aggregation of price responses across multiple markets. When markets are characterized by information asymmetry and market segmentation, price responses from a single market will result in a biased estimate of mean abnormal return, because the estimate will omit relevant information.

The GLS estimator above allows price responses to be pooled across markets, while avoiding double counting of observations by "downweighting" observations that are correlated. Further, the associated estimate has a straightforward interpretation. $\hat{\beta}_{GLS}$ estimates the mean of the distribution of unstandardized abnormal returns, β , and $Z_{\hat{\beta}_{GLS}}$ allows one to test the hypothesis that $\beta = 0$. Other commonly used tests, such as the *t*-statistics of Patell (1976), Boehmer, Musumeci, and Poulsen (1991), and Kolari and Pynnönen (2010), test hypotheses about the mean of the distribution of standardized abnormal returns.[6]

As is well-known, a major disadvantage of the GLS procedure with cross-sectional correlation is that it underestimates standard errors (Malatesta, 1986). Accordingly, $Z_{\hat{\beta}_{GLS}}$ is expected to over-reject the null hypothesis. A number of approaches for unbiased estimation of standard errors have been proposed to address this problem. Most recently, Kolari and Pynnönen (2010) propose a test statistic that compares well against a number of other test statistics, including both standardized and non-standardized test statistics, portfolio methods, and non-parametric rank tests. While their analysis focuses on cross-sectional correlation due to same-day announcements, it is conceptually identical to our problem.

In the context of our problem, we can rewrite K&P's Equations (1)-(3) as follows:

$$(52)\quad Var\left(\sum_i \sum_j \frac{\left(AR_{ijt} / \sigma_{ij} \right)}{N}\right) = \frac{1}{N^2}\left(\sum_i \sum_j Var\left(AR_{ijt} / \sigma_{ij} \right)\right) + \frac{1}{N^2}\sum_i \sum_{j \neq k} Cov\left(AR_{ijt} / \sigma_{ij} , AR_{ikt} / \sigma_{ik} \right)$$

$$= \frac{1}{N} + \frac{1}{N^2}\sum_i \sum_{j \neq k} \rho_{ij,ik} = \left(\boldsymbol{x}_t' \boldsymbol{x}_t \right)^{-1} \boldsymbol{x}_t' \tilde{\boldsymbol{\Omega}} \boldsymbol{x}_t \left(\boldsymbol{x}_t' \boldsymbol{x}_t \right)^{-1},$$

[6] Kolari and Pynnönen (2010, page 4002) allude to the fact that their test statistic is geared toward the distribution of standardized abnormal returns, in contrast to the distribution of (unstandardized) abnormal returns, when they state: "Thus, scaled returns should be used only for statistical testing purposes as signal detection devices of the event effect, while raw returns carry the economic information for interpretation purposes when a signal is detected.

where $\boldsymbol{x}_t$ is defined as above.[7]

The last term in Equation (52) should look familiar as the sandwich estimator (White, 1980). In fact, it is the sandwich estimator of the variance of the OLS estimator of γ in the model $\tilde{\boldsymbol{y}}_t = \boldsymbol{x}_t\gamma + \tilde{\boldsymbol{\varepsilon}}_t$, where $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\boldsymbol{0_N}, \tilde{\boldsymbol{\Omega}})$ (cf. Equation 27 above). As K&P note, the advantage of the sandwich estimator lies in the fact that the correlation parameters are averaged, so that any individual correlation makes a relatively small contribution to the estimate of the standard error. In contrast, GLS requires inversion of the variance-covariance matrix (cf. Equation 35), which can magnify the influence of individual correlation parameters. The more correlation parameters there are in the variance-covariance matrix, the more serious this problem.

Beck and Katz (1995) study the finite sample properties of an alternative sandwich estimator in a panel data setting where errors are characterized by heteroskedasticity, serial correlation, and cross-sectional correlation. They then compare this alternative estimator (the PCSE estimator) to GLS. Their Monte Carlo studies confirm that the GLS estimator underestimates the coefficient standard error, often severely so. In contrast, and like K&P, they demonstrate that a sandwich estimator greatly improves standard error estimation and produces accurate coverage rates in finite samples. Reed and Webb (2010) replicate Beck and Katz's experiments, confirming the superior performance of the sandwich estimator for coefficient standard errors, but show that GLS produces more efficient coefficient estimates.

Based on these studies, we can conclude that GLS is likely to produce better estimates of the mean of the distribution of unstandardized abnormal returns, but that a sandwich estimator should produce better estimates of its standard error. Accordingly, given the model $\tilde{\boldsymbol{y}}_t = \tilde{\boldsymbol{x}}_t\beta + \tilde{\boldsymbol{\varepsilon}}_t$, $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\boldsymbol{0_N}, \tilde{\boldsymbol{\Omega}})$ (cf. Equations 31 and 33), and following Kolari and Pynnönen (2010), Beck and Katz (1995), and Reed and Webb (2010), we also estimate β with

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

(cf. Equation 18), and calculate the corresponding sandwich estimator of its standard error,

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

with test statistic,

[7] In our model, the variance of the scaled abnormal returns, what K&P denote as σ_A^2, equals unity.

$$(55)\qquad Z_{\hat{\beta}_S} = \frac{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{y}}_t}{\sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}\tilde{\boldsymbol{x}}_t\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}}.$$

Note that $\hat{\beta}_S$ is the weighted (on heteroscedasticity) least squares estimator of β, and that $s.e.\left(\hat{\beta}_S\right) = \sqrt{\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}\tilde{\boldsymbol{x}}_t\left(\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{x}}_t\right)^{-1}}$ is the sandwich estimator of the corresponding standard error.

Generalization to a multiple-day testing period is straightforward. $\hat{\beta}_S$, while less efficient than $\hat{\beta}_{GLS}$, is expected to produce improved standard error estimates and more reliable hypothesis tests.

3. APPLICATION: OVERSEAS MERGERS AND ACQUISITIONS BY CHINESE FIRMS.

In this section, we (i) 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 and (ii) compare it to some other approaches.[8] There are two reasons why this should be a useful application for assessing the potential contribution of our generalized methodology. First, the geographical 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) 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

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

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. A total of 95 firms are represented in our sample. Sixteen, or approximately 17%, list on more than one exchange. The influence of cross-listing is, however, understated by this relatively small proportion, because cross-listed firms are much more likely to engage in OMAs: 46 of the 157 events (29%) are associated with cross-listed firms; as are 102 of the 213 observations in the full sample (48%). These data indicate the extent of the problem caused by cross-listing for conventional event-study methodology. If we restrict our analysis to only one observation per firm-event, we throw away over a quarter of all our observations (56 out of 213). Alternatively, the fact that almost half of all observations are associated with cross-listed firms means that the assumption of statistical independence across observations is not tenable for the pooled sample.

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.[9]

[9] Empirical studies show that correlation between different markets are relatively low: 0.0071-0.1232 for market return pairs (Wang, Gunasekarage, and Power, 2005); 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 and 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

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 trading obstacles have been cited as an explanation for the well-known discount of Hong Kong H shares relative to China A shares.[10]

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.[11] 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.

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

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international stock markets, whereas no other markets can significantly explain U.S. market movements (Eun and Shim, 1989; Hamao, Masulis, and Ng, 1990; Wang, Gunasekarage, and Power, 2005).

[10] 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.

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

percent for shares listed on the China Mainland - US markets.[12] 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 Alternative Approaches.

Once we are convinced that cross-listed returns provide useful information, it follows that event-study methodology should appropriately aggregate that information. The GLS estimator derived above provides two benefits. First, it allows the researcher to efficiently aggregate information across multiple markets without "double counting." Second, because it enables the use of cross-listed return data, 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 providing an example of the practical difference its use can make.

TABLE 4 reports estimates of the mean of the distribution of daily abnormal returns, β, over various test period intervals. The first two columns report estimates when using the "Home" (=China Mainland) and "Highest Volume" markets. The estimates are calculated using OLS (=AAR).[13] A comparison of these two columns illustrates the effect of expanding the number of observations and including information from different markets, holding the estimation procedure constant. The third column reports GLS estimates based on all observations, including cross-listed shares. The results in this column combine the effects of (i) expanding the number of observations with (ii) using a different estimator (GLS) of β. The fourth column reports the weighted least squares (WLS)/sandwich estimator results for the All Listings sample. We are particularly interested in comparing the Z-statistics from Columns (3) and (4) to identify the extent to which GLS underestimates standard errors in our application.

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[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 (MAPD) is: $P_{MAPD} = \frac{|p_1 - p_2|}{(p_1 + p_2)/2}$.

[13] Standard errors for the OLS estimator are calculated using Equation (10), with σ estimated by $\hat{\sigma} = \sqrt{\frac{\sum_{s=1}^{S}\sum_{i=1}^{N}\left(AR_{is} - \hat{\beta}_{OLS}\right)^2}{N(S-2)}}$ in keeping with the exposition in the text.

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 generate different estimates of β. In addition, it also increases the total number of sample observations (from 66 to 157).

A comparison of Columns (1) and (2) confirms that the Home sample finds that none of the testing intervals have abnormal returns that are statistically significant. In contrast, the Highest Volume sample finds significant ARs on both the (-1,1) and (2,5) windows. The absolute sizes of the estimated mean abnormal returns on these two windows, while modest, are approximately twice as large compared to the Home sample. The positive AAR value on the (-1,1) window indicates a favorable market response to the OMA announcement, while the negative AAR value on the (2,5) window -- of approximately equal but opposite size -- suggests overshooting and subsequent retrenchment following the announcement.

Column (3) reports the results of expanding the sample to include all observations, including all occurrences of multiple-listed shares; and using the GLS procedure. As before, the (-1,1) interval is positive and statistically significant, consistent with markets reacting positively to the news of an OMA. However, the estimate of mean abnormal returns on the (2,5) interval is substantially smaller in absolute value, and insignificant. The estimates of Column (4) are very similar to Column (3), and indicate that GLS has not substantially underestimated standard errors in these cases.[14] Thus, the use of cross-listed return data, and corresponding GLS procedure, lead to the conclusion that markets responded favourably to announcements of Chinese OMAs during this period, and that there was no subsequent, post-announcement reversal.

Are the differences between Columns (2) and (3) due to the use of different/more observations? Or due to the use of a different estimator? TABLE A.3 in the Appendix indicates that they are the result of using GLS rather than OLS (cf. Columns 3 and 4 in that table). When one uses OLS to estimate mean abnormal returns for the All Listings sample, the results are similar to those of the Highest Volume sample; both with respect to estimates

[14] Reed and Ye (2011) 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). This may explain why there is relatively little difference in the standard error estimates of Columns (3) and (4).

of mean abnormal returns, and their associated test statistics. In contrast, the GLS estimates produce smaller (in absolute value) estimates of mean abnormal returns on the (-1,1) and (2,5) windows, with only one significant interval.

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 and fourth column report GLS and WLS/sandwich estimates of β and its standard error using the All Listings sample. Estimates using the Home market sample find significant ARs on Day -1 (positive), Day 4 (negative), and Day 10 (negative). The Highest Volume sample produces significant ARs on Day -5 (positive), Day 2 (negative), and Day 3 (negative). In contrast, the All Listings sample yields a lone, positive significant AR; either on Day -1 (Column 3) or Day 1 (Column 4). Only the All Listings estimates produce a coherent story associated with the announcement of Chinese OMAs, albeit with slightly different interpretations. The GLS estimates of Column 3 suggest that there may be some information leakage prior to the announcement. In contrast, the results of Column 4 suggest that overseas markets may respond with a slight lag.

The preceding application has provided an empirical demonstration of how pooling return data from cross-listings of a firm's stock, in combination with employing the appropriate estimator, can produce substantially different estimates than conventional average abnormal returns. For example, the OLS(=AAR) estimates of TABLE 4 provide some evidence of a negative and significant reversal after an initial, positive announcement effect. In addition, the daily AR results from TABLE 5 show unusual patterns of significant ARs outside the (-1,1) announcement window. These anomalous results disappear when GLS is applied to the All Listings data.

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 cross-listed shares of the same firm can be included. This allows not just more, but potentially different information to be included. A second reason is that GLS makes efficient use of the information in the larger sample.

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 a generalized least squares (GLS) procedure that efficiently incorporates the relationship of share price performance across multiple exchanges. One disadvantage of GLS is that it is known to underestimate standard errors in the presence of cross-sectional correlation (Malatesta, 1986; Beck and Katz, 1995; Kolari and Pynnönen, 2010). To address this problem, we also provide a corresponding sandwich estimator (White, 1980) of the standard error.

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 find that our GLS procedure eliminates a number of anomalous results associated with conventional average abnormal returns (AAR) estimates. We argue that 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 cross-listed observations. This approach is likely to be particularly relevant for studies involving emerging markets, where information asymmetry and market segmentation are likely to be significant features.

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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***
$\boldsymbol{\rho_{ij,ik}}$: ***i = China Mainland*** ***j = US***	10	0.121	0.101	-0.081	0.493
$\boldsymbol{\rho_{ij,ik}}$: ***i = China Mainland*** ***j = Hong Kong***	16	0.090	0.092	-0.173	0.376
$\boldsymbol{\rho_{ij,ik}}$: ***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)*	$\hat{\beta}_{S}$ *(4)*
(-5,-2)	0.0019 (1.21)	0.0004 (0.27)	0.0007 (0.92)	0.0003 (0.38)
(-1,1)	0.0025 (1.47)	0.0040** (2.13)	0.0022** (2.55)	0.0022** (2.46)
(2,5)	-0.0016 (-1.11)	-0.0032*** (-2.64)	-0.0007 (-0.95)	-0.0006 (-0.73)
(-5,5)	0.0008 (0.86)	0.0001 (0.09)	0.0006 (1.31)	0.0005 (1.07)
(-10,10)	0.0005 (0.90)	0.0000 (002)	0.0003 (0.89)	0.0002 (0.54)

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)***	***HIGHEST VOLUME (157 Obs)***	***ALL LISTINGS (213 Obs)***	
	$\hat{\beta}_{OLS} = AAR$ *(1)*	$\hat{\beta}_{OLS} = AAR$ *(2)*	$\hat{\beta}_{GLS}$ *(3)*	$\hat{\beta}_{S}$ *(4)*
-10	0.0007 (0.24)	0.0026 (1.05)	0.0019 (1.29)	0.0018 (1.20)
-9	0.0033 (1.27)	0.0025 (1.12)	0.0019 (1.28)	0.0021 (1.36)
-8	0.0013 (0.57)	-0.0003 (-0.12)	-0.0001 (-0.04)	-0.0003 (-0.21)
-7	0.0002 (0.09)	-0.0031 (-1.61)	-0.0010 (-0.67)	-0.0015 (-0.95)
-6	-0.0009 (-0.26)	-0.0017 (-0.62)	-0.0021 (-1.39)	-0.0023 (-1.51)
-5	0.0040 (1.39)	0.0061* (1.97)	0.0011 (0.74)	0.0006 (0.39)
-4	0.0021 (0.64)	-0.0024 (-0.82)	0.0013 (0.90)	0.0013 (0.84)
-3	-0.0001 (-0.03)	0.0000 (0.01)	0.0010 (0.65)	0.0004 (0.23)
-2	0.0015 (0.43)	-0.0022 (-0.78)	-0.0007 (-0.46)	-0.0011 (-0.69)
-1	0.0088*** (2.75)	0.0036 (1.55)	0.0028* (1.86)	0.0022 (1.43)
0	0.0009 (0.33)	0.0044 (0.99)	0.0016 (1.07)	0.0012 (0.80)
1	-0.0021 (-0.73)	0.0040 (1.51)	0.0022 (1.48)	0.0031** (2.02)
2	-0.0048 (-1.50)	-0.0060** (-2.26)	-0.0011 (-0.77)	-0.0013 (-0.85)

DAY	***HOME (66 Obs)***	***HIGHEST VOLUME (157 Obs)***	***ALL LISTINGS (213 Obs)***	
	$\hat{\beta}_{OLS} = AAR$ ***(1)***	$\hat{\beta}_{OLS} = AAR$ ***(2)***	$\hat{\beta}_{GLS}$ ***(3)***	$\hat{\beta}_{S}$ ***(4)***
3	-0.0004 (-0.12)	-0.0056** (-2.29)	-0.0018 (-1.18)	-0.0019 (-1.26)
4	-0.0050** (-2.04)	-0.0024 (-1.11)	-0.0014 (-0.95)	-0.0008 (-0.53)
5	0.0037 (1.40)	0.0013 (0.58)	0.0015 (1.00)	0.0018 (1.18)
6	-0.0001 (-0.04)	-0.0017 (-0.83)	-0.0003 (-0.22)	-0.0003 (-0.19)
7	0.0025 (1.00)	0.0045 (1.41)	0.0007 (0.49)	0.0005 (0.32)
8	0.0015 (0.57)	0.0005 (0.18)	0.0014 (0.97)	0.0012 (0.77)
9	-0.0020 (-0.93)	-0.0006 (-0.28)	-0.0013 (-0.90)	-0.0012 (-0.80)
10	-0.0037* (-1.69)	-0.0031 (-1.54)	-0.0016 (-1.08)	-0.0016 (-1.06)

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)*	$\hat{\beta}_{S}$ *(5)*
(-5,-2)	0.0019 (1.21)	0.0004 (0.27)	0.0001 (0.07)	0.0007 (0.92)	0.0003 (0.38)
(-1,1)	0.0025 (1.47)	0.0040** (2.13)	0.0044*** (2.91)	0.0022** (2.55)	0.0022** (2.46)
(2,5)	-0.0016 (-1.11)	-0.0032*** (-2.64)	-0.0023** (-2.29)	-0.0007 (-0.95)	-0.0006 (-0.73)
(-5,5)	0.0008 (0.86)	0.0001 (0.09)	0.0004 (0.58)	0.0006 (1.31)	0.0005 (1.07)
(-10,10)	0.0005 (0.90)	0.0000 (002)	0.0003 (0.59)	0.0003 (0.89)	0.0002 (0.54)

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)***	$\hat{\beta}_{S}$ ***(5)***
-10	0.0007 (0.24)	0.0026 (1.05)	0.0026 (1.37)	0.0019 (1.29)	0.0018 (1.20)
-9	0.0033 (1.27)	0.0025 (1.12)	0.0026 (1.29)	0.0019 (1.28)	0.0021 (1.36)
-8	0.0013 (0.57)	-0.0003 (-0.12)	-0.0004 (-0.22)	-0.0001 (-0.04)	-0.0003 (-0.21)
-7	0.0002 (0.09)	-0.0031 (-1.61)	-0.0033* (-1.92)	-0.0010 (-0.67)	-0.0015 (-0.95)
-6	-0.0009 (-0.26)	-0.0017 (-0.62)	-0.0012 (-0.55)	-0.0021 (-1.39)	-0.0023 (-1.51)
-5	0.0040 (1.39)	0.0061* (1.97)	0.0051** (2.10)	0.0011 (0.74)	0.0006 (0.39)
-4	0.0021 (0.64)	-0.0024 (-0.82)	-0.0015 (-0.62)	0.0013 (0.90)	0.0013 (0.84)
-3	-0.0001 (-0.03)	0.0000 (0.01)	-0.0005 (-0.28)	0.0010 (0.65)	0.0004 (0.23)
-2	0.0015 (0.43)	-0.0022 (-0.78)	-0.0028 (-1.23)	-0.0007 (-0.46)	-0.0011 (-0.69)
-1	0.0088*** (2.75)	0.0036 (1.55)	0.0033* (1.72)	0.0028* (1.86)	0.0022 (1.43)
0	0.0009 (0.33)	0.0044 (0.99)	0.0044 (1.29)	0.0016 (1.07)	0.0012 (0.80)
1	-0.0021 (-0.73)	0.0040 (1.51)	0.0054** (2.42)	0.0022 (1.48)	0.0031** (2.02)

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)	$\hat{\beta}_{S}$ (5)
2	-0.0048 (-1.50)	-0.0060** (-2.26)	-0.0052** (-2.30)	-0.0011 (-0.77)	-0.0013 (-0.85)
3	-0.0004 (-0.12)	-0.0056** (-2.29)	-0.0047** (-2.38)	-0.0018 (-1.18)	-0.0019 (-1.26)
4	-0.0050** (-2.04)	-0.0024 (-1.11)	-0.0010 (-0.56)	-0.0014 (-0.95)	-0.0008 (-0.53)
5	0.0037 (1.40)	0.0013 (0.58)	0.0018 (0.99)	0.0015 (1.00)	0.0018 (1.18)
6	-0.0001 (-0.04)	-0.0017 (-0.83)	-0.0002 (-0.01)	-0.0003 (-0.22)	-0.0003 (-0.19)
7	0.0025 (1.00)	0.0045 (1.41)	0.0034 (1.35)	0.0007 (0.49)	0.0005 (0.32)
8	0.0015 (0.57)	0.0005 (0.18)	0.0010 (0.48)	0.0014 (0.97)	0.0012 (0.77)
9	-0.0020 (-0.93)	-0.0006 (-0.28)	-0.0004 (-0.22)	-0.0013 (-0.90)	-0.0012 (-0.80)
10	-0.0037* (-1.69)	-0.0031 (-1.54)	-0.0028* (-1.66)	-0.0016 (-1.08)	-0.0016 (-1.06)

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

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.