A Study of Chinese Overseas Mergers and Acquisitions: 1994-2009

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Abstract

The effect of government intervention on business is a longstanding topic in political economy. One of the interesting cases is in recent China, where "socialism with Chinese characteristics" is associated with three decades of rapid economic growth. However, many doubt the sustainability of the "dual-track" approach applied in China, which tries to combine "market track" and "planned track" and achieve national goals without sacrificing firm-specific efficiency.

This thesis investigates how the "market economy model dominated by political capital" works in Chinese OMAs. We look at Chinese overseas M&As in the period of 1994-2009. It is a good example because 80% of Chinese overseas M&A took place after China's "Go Global" policy, and approximately half of the executors are state-owned enterprises. We test whether China's Go Global policy affected shareholders' wealth while pursuing government's long-term goals of strategic resource-seeking and industry restructuring.

The results show that Chinese OMAs achieved significantly positive performance in the short-run. However, performance decreased and became statistically insignificant over a longer three-year horizon. We find no evidence in the short-run responses of markets that the Go Global policy sacrificed shareholder wealth. However, we find OMAs by state-owned enterprises significantly underperformed private enterprises in the three years following completion of the deal. And there is evidence OMA performance varied across different sectors in the before and after policy periods.

We also develop a generalized event study approach that pools multi-listings in event samples and "weights" individual listings by the new information they provide. We think this approach can be applied to other empirical studies in international/emerging markets settings.

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Abbreviations

AAR	Average Abnormal Return
ACAR	Average Cumulative Abnormal Return
AMEX	American Stock Exchange
ASCAR	Average Standardized Cumulative Abnormal Return
BHAR	Buy and Hold Abnormal Return
BM	Book to Market Ratio
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
CPE	Cumulative Prediction Error
CTAR	Calendar-time Abnormal Return
FDI	Foreign Direct Investment
FF3FM	Fama and French Three Factor Model
GDP	Gross Domestic Product
GLS	Generalized Least Square
HML	High Minus Low, the book to market equity factor in FF3FM
M&A	Merger and Acquisition
MBR	Market to Book Ratio
MMAR	Mean Monthly Abnormal Return
MNE	Multinational Enterprise
MOC	Ministry of Commerce
MSCI	Morgan Stanley Capital International
MV	Market Value
NASDAQ	National Association of Securities Dealers Automated Quotations System
NYSE	New York Stock Exchange

OFDI	Outward Foreign Direct Investment
OLS	Ordinary Least Square
OMA	Overseas Merger and Acquisition
PSR	Patell Standardised Residual
R&D	Research and Development
S&P	Standard and Poor’s
SAFE	State Administration of Foreign Exchange
SMB	Small Minus Big, the size factor in FF3FM
SOE	State-owned Enterprise

Chapter One Introduction

1.1. Why China, Why OMA?

China's modernization and prosperity over the last three decades has been described as the "China Miracle". Since economic reform and open policy in China, the Chinese gross domestic product (GDP) has grown at an average annual rate of 9.8 percent according to official statistics (Chang, 2008). What is more, the rate of growth seems to be accelerating with an increasing trade surplus and foreign exchange reserves.

Yet by each of the criteria that westerners considers crucial to economic success, China scores poorly or worse. Outsiders criticize Chinese growth pattern for grafting a free-market mechanism onto a Marxist structure. They argue that a true market economy requires the rule of law, which in turn requires institutional restraints on government. However, the communist party in China insists on remaining above the law, and "attempt to reform a system that is essentially unreformable"; as they are unlikely to tolerate more development of the various private sectors (Chang, 2008).

In fact, the Chinese government attributes the success of the country's three-decade rapid economic development to "socialism with Chinese characteristics". This approach can be described as a "market economy model dominated by political capital". It is characterized by a strategy of utilizing government's coercive power to cultivate national brands and global players. It places a premium on quick-witted decision-making in investment, especially construction in transportation and infrastructure.

With common wealth in control (so-called government capitalization), the Chinese government supports domestic companies in "pillar industries" to Go Global to keep more of the rewards in China. At the firm-specific level, this is a different approach than that of efficiency-seeking businesses. The latter rationalise the structure of established resources in such a way that the investing companies can gain from the common governance of geographically dispersed activities.

In this thesis, we analyze Chinese overseas mergers and acquisitions (OMAs) with a view to evaluating the effect of government's political policy on Chinese OMA activities.

1.1.1 "Three Carriages" in Chinese Economic Development

The so-called "Three Carriages" in Chinese economic development are investment, export, and consumption. Initially, investment has been the focus of government attention. Apart from overseas investment, much investment on public facilities has been aimed at supporting the domestic economic environment, with the intent of creating a multiplier effect on gross domestic product (GDP).

The second carriage is export. It is believed that a large trade surplus contributes to economic prosperity, and accelerates the growth of manufacturing industries. However, as an emerging economy, ordinary Chinese people do not enjoy strong support from a social insurance system. As a result, citizens need to worry about expenditure on education, healthcare and housing, which limits their consumption power.

Chinese labour-intensive products are well known in world markets. However, the unwanted by-products of this kind of export-oriented economy are pollution and energy consumption. Trade conflict is another consideration. Economists argue China's current economic development pattern is not sustainable. And that overseas M&A is a possible solution for industry restructuring and trade substitution.

1.1.2. Motives of Chinese OMAs

OMAs provide a means whereby the Chinese economy can acquire strategic resources for sustainable growth. Examples of strategic resources are energy, land or human resources. It is also regarded as a learning process for technology improvement and industry upgrading

(Cantwell, 1989). Intangible assets such as patents, property rights and brands are also critical resources in competitive markets. OMAs can speed up the growth of Chinese multi-national enterprises (MNEs) by gaining control of these.

OMAs are also a path to create and expand markets. Traditional Foreign Direct Investment (FDI) theories suggest that overseas M&As perform as trade substitution (Buckley & Casson, 1976; Hymer, 1960; Vernon, 1966). Firms achieve foreign market share by operating subsidiaries in the host countries instead of exporting. Meantime, some Chinese enterprises serve as parts and auxiliary-equipment manufacturers for developed multinational giants. To provide more convenient service and gain market share in the foreign markets, they are tempted to move to the developed countries (Lall, 1983; Lecraw, 1993; Wells, 1983b).

Chinese OMAs are easily funded by excessive liquidity. Mergers and acquisitions occur when the economy is booming, and free cash flow encourages managers of firms to expand their market power and managerial scale (Jensen & Meckling, 1976). With the accumulated wealth of 3 decades of economic growth - and the associated savings of households, enterprises and governments - Chinese MNEs are easily financed in OMA activities.

Finally, Chinese Overseas M&As can be one of the solutions to mitigate pressure on RMB appreciation, which derives from the huge foreign exchange reserves of China. U.S. dollar assets constitute the bulk of Chinese foreign exchange reserves. As the U.S. dollar has depreciated over time, Chinese MNEs find it cheaper to purchase foreign assets and are more likely to invest abroad.

1.1.3. Motives of This Research

In contrast with the large scale of overseas M&A studies in developed countries, little research has been conducted on overseas M&As from emerging economies. Some researchers have noticed considerable overseas investment from emerging economies over the last few decades. However, their focus has been the motivations of foreign direct investment (FDI), and theories on location and industry distribution. Few of them employ empirical analysis to investigate Chinese overseas M&A performance and determinants.

However, it is a critical research topic to examine Chinese OMA performance and their determinants. From the perspective of economic development, it is a good example to see to what extent government intervention can influence business activities. At the firm-specific level, it provides an opportunity to study how government policy affects shareholder wealth. This research enriches knowledge of OMAs in emerging market settings. Top managers and policy makers in similar economic setting can also get useful information from an analysis of the determinants of OMA performance.

In all, China's open and reform policy in the past decades has created a better economic environment for domestic firms to expand overseas, which is consistent with John Dunning's dynamic FDI development theory (Dunning, Kim, & Lin, 2001). The Chinese economy is now integrating with the world. The growth pattern of China and Chinese overseas M&A activities needs to be better understood by the rest of the world, which is the reason we choose it as the thesis topic.

1.2. Introduction of Chinese OMAs[1]

Chinese firms started overseas M&A activity in the mid 1980s. There are four major waves of Overseas M&As. The first wave (1994-1998) was triggered by the return of Hong Kong to China, as money from the mainland flowed into Hong Kong to take control of strategically important assets in the city. The second wave (1999-2002) is characterized by

[1] The main data sources for Chinese OMAs are Thomson's SDC Platinum M&A Database. We also take reference from World Investment Report (2010, 2009), Morck, Yeung & Minyuan (2008) and Hemerling, Michael D. & Michaelis (2006).

Chinese companies buying out their foreign partners. The third wave (2002 and after) emerged after the Go Global policy was adopted as part of the 10th Five Year Plan, along with government announcements of loosening controls on outward investment by Chinese firms. In this period, Overseas M&A activities have covered a far broader range of industries and target countries with larger deal size (please see Figure 2 in Chapter Three for details). A fourth wave of Chinese OMAs occurred after the global financial crisis (2007 and after). 44.6% of the OMA deals, and 29.8% of total deal value happened during the fourth wave.[2] World Investment Reports lists the Chinese mainland as ranked 6th of the top 20 home economies in global FDI outflows in the year 2009, compared to 13th in 2007 (*World Investment Report*, 2009; 2010).

Natural Resources and High-Technology industries lead the recent Chinese OMA wave with 66% of total deals.[3] The rapid increase in natural resource OMAs (3% during the pre-policy period to 33% of total deals in the post-policy period) is driven by China's quest for sufficient supplies of energy and other natural resources to fuel its rapid development. As an integral part of a modern industrial infrastructure, advanced technologies are regarded as strategic resources for sustainable growth. High-Technology industries are high-value added, less energy-consuming and low pollution. They are pillar industries for government's goal of industry modernization.

Developed targets account for approximately 68.8% of deal numbers and 64.9% of the total deal value of Chinese OMAs.[4] The extraordinarily large share of 74.2% Hong Kong targets in the pre-policy period declined to 27.8% after the Go Global policy.[5] Of the Natural resources industries, the primary industry targets are located mostly in South-east Asia,

[2] Please see Table 1 in Chapter Three for details.
[3] Please see Table 13 in Chapter Three for details.
[4] Please see Table 2 in Chapter Three for details.
[5] Please see Table 13 in Chapter Three for details.

Russia and in Africa; whereas the mineral targets are located in South America and Australia. The targets in manufacturing industries tend to be in nations with high trade barriers, while service industry targets tend to be in developed and emerging economies.

1.3. Research Design

This thesis is arranged according to four main research tasks: (i) To evaluate short-and long-run performance of Chinese OMAs in stock markets. (ii) To test the effects of the Go Global policy on OMA performance. (iii) To investigate the determinants of OMA performance. (iv) To develop an econometric approach to include multi-listings in event studies of OMA performance.

Firstly, we are interested in whether Chinese OMAs create value for shareholders in the short- and long-run. We employ standard event study methodologies to test stock market performance of Chinese acquirers.

Secondly, we exam how the Go Global policy affects Chinese OMA performance. We break the whole sample into pre- and post-policy period and employ (i) multi-variate regression and (ii) a Blinder-Oaxaca Decomposition procedure to accomplish this goal.

Thirdly, we test the relationship between OMA performance and determinants. We group performance determinants into three categories: bidder's endowment, transaction details, and target location variables. Univariate and multivariate regression are used to investigate the respective relationships.

Lastly, we develop a procedure to include multi-listings in event studies. Cross-listings provide additional information. And in emerging market setting, these listings usually mean more transparent firms' financial statements and a better investor's protection environment. Moreover, the inclusion of more observations is especially valuable for emerging markets, where sample size and time series data are limited for standard empirical study. If we can correct the heteroscadesticity and cross-sectional correlation in multi-listings, it is possible to put multi-listings in the sample pool and obtain better estimates.

1.4. Findings

We report our finding in three research chapters. Chapter Three employs daily data to investigate the Go Global policy and its impact to Chinese short-run OMA performance. We find that over the 1994-2009 period, abnormal returns are positive and significant on the (-1,1) interval. However, markets responded less favourably to Chinese OMAs after the Go Global policy. We investigate three hypotheses: (i) the Demand and Supply Hypothesis, (ii) the Government Capitalization Hypothesis, and (iii) the Hubris and Herding hypothesis. We find no evidence in favor of the “government capitalization” or “hubris and herding” hypothesis. We conclude that the deregulation of overseas investment after “Go Global” era increased the number of deals, which had the effect of decreasing inframarginal rents associated with those deals.

Chapter Four looks at long-term OMA performance and their determinants. Monthly data are employed to examine one-, two- and three-year calendar-time abnormal returns (CTARs) after Chinese OMAs. The Fama-French Three Factor Model is generally supported on asset pricing in our dataset. We find some evidence of positive one- and two-year CTARs, though the results are not significant. However, by the third year after an OMA event, these returns become very small, and remain insignificant. We note OMA performance varies across different sectors. The Chinese trade sector suffered a significant drop in OMA performance in the post-policy period. Further, short-and long-run performance determinants differ. We also find that government ownership is negatively and significantly related to long-run performance as measured by yearly CTAR.

Chapter Five develops a new methodology for event studies that allows multi-listings. This approach suits empirical studies in emerging economies where markets are partially segmented, and relatively few observations can be collected in a short period of time. We use GLS to "weight" multi-listings according to the new information they provide, such that consistent and asymptotically efficient estimates of abnormal returns are produced. We apply the new approach on Chinese OMA daily data. The results show significant, positive abnormal returns on the (-1,1) window, but the estimate of CARs falls from over 1 percent to approximately 0.2%. We suggest that this new approach may be useful in other emerging market research situations.

1.5. Contribution

This thesis focuses on stock market performance of Chinese acquirers on overseas M&A events (OMAs) from 1994 through 2009. Our research contributes to the literature in the following ways:

(i) We investigate how the "market economy model dominated by political capital" works in Chinese OMAs. We find that the Go Global policy speeds up Chinese OMAs by number and scale. Half of all OMAs are initiated by political capital. We find no evidence that this government policy destroys OMA value in the short-run. Nor is there evidence that top-manager's irrational expansion adversely affects short-run OMA performance. However, in the long-run, political capital (government ownership) is found to be significantly and negatively related to performance. This suggests that greater reliance on private capital involvement would be good for OMA performance and sustainable growth.

(ii) Our study uses the largest sample size to date to study Chinese short- and long-run OMA performance.

(iii) Our study expands the analysis of OMAs beyond domestic listings to include listings on foreign markets (Hong Kong and the U.S.). Our results evidence that Chinese multi-listings supply useful additional information about market evaluations of Chinese OMAs.

(iv) We develop a new procedure for conducting event studies using multi-listing information. We believe this approach can be applied to other empirical studies in segmented/emerging market settings.

1.6. Thesis Framework

This thesis is arranged by six chapters. Chapter Two is an introduction to the literature related to my thesis. Chapter Three employs daily data to investigate the effect of the Go Global policy on the short-run performance of Chinese overseas M&As. Chapter Four looks at long-term OMA performance and their determinants with monthly data. Chapter Five introduces a new methodology in event study analysis to include multiple listings and applies it to a Chinese OMA sample. Chapter Six concludes.

Chapter Two Literature Review

This chapter reviews the extensive literature on mergers and acquisitions (M&As) as it relates to our topic of Chinese overseas M&As (OMAs). Our review consists of four sections: (i) Motives, (ii) Methodology, (iii) Performance and (iv) Determinants.

Motives of Chinese Overseas M&As (OMA). OMAs are strategic investment decisions of multinational enterprises (MNEs). These decisions are driven by many motivations. A major difference between Chinese OMAs and those of developed countries is the substantial role that government plays. Government policies heavily influence Chinese OMA decision-making. The motivation of Chinese firms to engage in OMAs needs to be understood within this context.

Event study and assets pricing models. Our analysis employs event study methodology and asset pricing models to evaluate short- and long-run performance of Chinese OMAs. In this section, we highlight the theory we employed. We also discuss alternative methodologies that have been employed in the literature.

OMA performance. An extensive literature reports on the performance of OMAs. These studies obtain different results depending on whether (i) the acquirer or (ii) the target is from a developed country. Emerging OMA acquirers are less likely to achieve positive abnormal returns. Most studies find negative or zero long-run OMA performance for acquirers. There is some evidence that targets fare better.

OMA Determinants. A large literature investigates the determinants of OMA performance. These determinants can be grouped into three categories. Bidder's endowment variables measure characteristics of the bidder, such as firm size, whether the firm is a "value firm", and its ownership structure. Transaction detail variables include things such as how the bidder financed the OMA deal, and whether professional advisors were employed. Finally, target location variables measure characteristics of the target firm and its resident country, such as inward/outward investment policies in host/home countries (country risk), culture differences and exchange rate factors.

2.1. Motives of Chinese OMAs

From corporate finance point of view, the motivation of OMAs is to make the investing enterprise more profitable and competitive in the markets it serves. Hopkins (1999) sorts the motives of domestic M&As into four categories, strategic motives, market motives, economic motives and personal motives. For cross-border M&As, he argues that firms' sources of competitive advantage in the global market come from national differences, scale economies and scope economies.[6] Moreover, the motives for cross-border M&A (global strategy) lay in achieving efficiency in current operations, managing risks and in innovation and adaptation.

Behrman (1972) concludes four basic motives of Overseas M&As. They are natural resource-seeking, market-seeking, efficiency-seeking and strategic asset or capability-seeking.[7] Natural resource-seeking means MNEs are prompted to invest abroad to acquire particular and specific resources of a higher quality at a lower real cost than could be obtained in their home countries. Market-seeking OMAs aim to sustain or protect existing markets or to exploit or promote new markets. The efficiency-seeking OMAs' goal is to rationalise the structure of established investment to achieve economies of scale and scope, and risk diversification. The strategic asset or capability-seeking is to promote MNE's long-term strategic objectives by acquiring the assets of foreign corporations.

Studies that focus on Chinese OMAs emphasize the resource and strategic asset seeking motivations of Chinese MNEs. Deng (2009) argues that more Chinese companies are using cross-border merger and acquisition to access resource and strategic assets so as to address

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[6] "Economies of scale" refers to reductions in unit cost of *a single* product as the size of a facility and the usage levels of other inputs increase. "Economies of scope" refers to lowering average cost for a firm in producing *two or more* products. It makes product diversification efficient if they are based on the common and recurrent use of proprietary knowhow or on an indivisible physical asset.

[7] Apart from the above four motivations of OMAs, Dunning (2008) rises the concept of "escape investment". He argues that the "round-tripping" of investment between China and Hong Kong to exploit incentives granted only to foreign investors. OMAs may be an escape strategy to tax or other government regulations.

their competitive disadvantages. Rui & Yip (2008) suggest that Chinese firms strategically use OMAs to acquire strategic capabilities, make use of institutional incentives and minimize institutional constraints.[8]

Antkiewicz and Whalley (2007) argue that the main motives for Chinese OMAs are related to recent changes in official Chinese policy that encourage domestic companies to invest abroad for the purpose of securing domestic energy demand as well as acquiring advanced technology.

Much OMA activities have been undertaken either directly by nation states, or with their support and encouragement.

> "Governments of the investing countries are also interested in the outcome of the activities of MNEs, then, by influencing the conduct of such firms or their affiliates, they may affect the amount and pattern of FDI." (Dunning, 2008)

Svedberg (1982) reveals that most early British investments in North America and 19th century investments by European colonial powers in the developing countries were government orientated. Sauvant (2005) shows some evidence that SOEs from Brazil & Russia are becoming more active as foreign investors.

Dunning (2008) argues that governments may affect the capacity and willingness of domestic firms to extend themselves to overseas markets by creating new incentives or structures; and influencing market conditions. In China, the Chinese government's decision to "go global" is targeted towards industry restructuring and increasing national competitive power by appealing to national interest. Based on this principal strategy, a series of

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[8]For example, lack of developed intellectual property rights frequently discourages firms to maximize their effort in R&D, despite government's efforts of encouraging and supporting numerous R&D projects at different times. This led to low R&D investment and technology level, and eventually the motive of Chinese firms to access the need from foreign companies.

promotional measures were announced in the several years following 2000.[9] Firstly, foreign exchange controls were relaxed. After the regulations “Notice on Simplifying Foreign Exchange Administration relating to OFDI 2003”, “Further Measures on Foreign Exchange Administration Stimulating OFDI 2005”, and “Supplement Measures of Foreign Exchange Usage for OFDI 2006”, the quota for purchasing foreign exchange for overseas investments was revoked and the necessary foreign exchange for domestic investors to invest abroad was extended to self-owned foreign exchange, the foreign exchange purchased by RMB, and domestic and overseas foreign exchange loans.

The second promotional measure was tax relief, and credit/loans support. A guidance catalogue was issued by the Ministry of Commerce (MOC). Firms complying with these requirements receive preferential treatment in situations concerning funding, tax collection, foreign exchange, customs, etc.

Thirdly, the Chinese government transformed its role from being a regulator of OMAs to being a supporter of OMAs. Approval processes were simplified, the threshold sums of OMA projects degraded, and an information bank set up to provide guidance and coordination of firms’ OMAs.

Luo, Xue and Han (2010) develop the logic that Chinese OMA policies are economically imperative and needed to offset the competitive disadvantage of Chinese MNEs in global competition. In terms of the eclectic paradigm, OMA promotion policies strengthen O-specific advantage of MNEs in the world market.[10] Further, the institutional environment in China magnifies the effects of the “Go global” policy because many Chinese MNEs are state-owned enterprises or have considerable government ownership.

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[9] Details of comprehensive extant OFDI Policy Regime in China please see Table 1 in Y. Luo et al. *How emerging market governments promote outward FDI: Experience from China*, Journal of world business 45 (2010), page 73-74.
[10] O-specific advantage comes from Dunning’s Ownership advantage in his eclectic paradigm. Please see Dunning and Lundan (2008), page 95-109 for details.

We conclude from our reading of the literature on Chinese OMAs that the motives of Chinese OMAs are primarily based on seeking resources and strategic assets. The long-term economic and political goals of the Chinese government are the main purpose of OMAs, not the short-term profitability interests of shareholders. However, as individual firms are critical components of a market economy in the long run, government strategic goals must be consistent with firms' performances. Positive short- and long-run shareholders' abnormal returns are the prime detector of appropriate OMA decision-making.

2.2. Event Study and Asset Pricing Models

Under the weak form of the efficient markets hypothesis, M&A announcements are information shocks that affect stock market prices. Econometricians have developed "event study" methodologies to capture investors' responses to M&A events, and evaluate M&A performance accordingly. They believe the magnitude of abnormal performance at the time the event actually occurs is a measure of the impact of the respective event on the wealth of firms' claimholders.

2.2.1. Event-time Approach

Most event studies have focused on the behaviour of share prices in order to test whether their stochastic behaviour is affected by the disclosure of firm-specific events.[11] Time series returns are split into an estimation period and a test period. daily abnormal returns are calculated by subtracting expected returns from actual returns during the test period (Norman, 1992).

(1) $AR_{it} = R_{it} - E(R_{it})$

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[11] See Norman Strong, *Modeling abnormal returns: a review article*, Journal of Business Finance & Accounting, June 1992, page 533-553.

Researchers use different benchmarks to calculate expected abnormal returns. Examples are mean adjusted returns, market adjusted returns, returns produced from the capital asset pricing model, returns from a control portfolio, and predicted returns from the market model. Of these, the market model is the most popular.

Under the market model, researchers estimate the following specification,

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

where *i* indicates a specific share, *t* is a day during the estimation window and R_{mt} is the observed return of an appropriate market portfolio at time *t*.

The coefficients estimated from this regression, $\hat{\alpha}_i$ and $\hat{\beta}_i$ are then used to calculate expected or predicted, returns during the test window.

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

Interval abnormal returns aggregate daily abnormal returns for specified intervals around the announcement date.

2.2.1.1. Abnormal Return Measurement

Brown and Warner (1980; 1985) analyse monthly/daily returns and use simulation procedures to examine various methodologies which are used in event-time approach. They compare the performance of the market model with methodologies using Fama-MacBeth residuals and control portfolios. [12] [13] They find the market model outperforms the more complicated Fama-MacBeth and control portfolio methods.

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[12] There are different versions of CAPM in empirical studies. Black, Jensen and Scholes (1972) prefer a constant beta approach, which implies the betas for portfolios are constant over the full period. However, Fama and MacBeth argue that betas are non-stationary. The *t*-statistics are biased upward under constant bata assumption. In their approach, the portfolio betas differ by estimating according to different time periods (generally 60 past daily/monthly data points). Therefore their estimation automatically corrects for cross-sectional correlations in the return errors by calculating realized parameter variance. Please see Fama and MacBeth (1973) for details. However, academic papers have tended to use the simpler approach of employing the full sample to estimate one constant beta for each portfolio.

As the timing of an event is not known precisely in some cases, event dates are not identified with certainty. using interval abnormal returns is a way to avoid the risk of missing an the event. Researchers employ two ways to calculate cumulative abnormal returns (CARs). Some researchers (Brown & Warner, 1980; Keown & Pinkerton, 1981) sum up cumulative daily abnormal returns in the test period, say from day (-30) till day (30) as follows:[14]

(4) $CAR_t = CAR_{t-1} + AR_t$

The associated cumulative abnormal returns should be a random walk before the announcement date. It jumps dramatically on day 0, with no further drift thereafter.

Other researchers (Aybar & Ficici, 2009; J. Doukas & Travlos, 1988; Mikkelson & Partch, 1986) investigate different interval cumulative abnormal returns for each security *i*. Example intervals are days (-60,-2), or days (1, 20). In general, the interval begins with day T1 and ends with T2, where T1 and T2 are specific to event announcements.[15] The formula is as follow:

(5) $CAR_{it} = \sum_{t=T1}^{T2} AR_{it}$

A finding of significant cumulative abnormal returns over the interval (-1,1) indicates the event has increased or decreased wealth. If significant cumulative abnormal returns are observed before the announcement date, for example days (-20,-2), or days (-10,-5), it implies information leakage before the announcement. A finding of significant CARs after the

[13] Control portfolios approach is to form the sample securities into a portfolio with an estimated β of 1. Regardless of the risk level of each sample security, the portfolio thus formed should have the same risk as the market portfolio. Those securities comprising the market portfolio become a "control portfolio" in the sense that the market portfolio has the same risk level as the sample securities, but is not experiencing the "event" under study. The performance measure for day/month 0 is the difference between the average return on the market portfolio on the day/month in which the sample securities experience events.

[14] Please also see Pettway, Sicherman, & Spiess (1993).

[15] For details, please see Fama, Fisher, Jensen, & Roll (1969; 1997) and Firth (1997).

announcement date, say days (1, 5) or days (5,10) suggests that the release of information may have been delayed.

2.2.1.2. Hypothesis Testing

The purpose of hypothesis testing in event study is to determine whether abnormal returns on the announcement day, or during intervals around the announcement day, are significantly different from zero. Brown and Warner (1980; 1985) find that parametric *t*-tests achieve higher rejection rates than non-parametric tests (e.g. the sign test and the Wilcoxon signed rank test). Standard parametric tests are perform well under (i) non-normality of daily returns, (ii) bias in OLS estimates of market model parameters in the presence of non-synchronous trading, (iii) autocorrelation in daily excess return and variance increases on days around an event.

Patell (1976) argues that when parameters of the market model are estimated from observations outside the test period, abnormal returns are prediction errors rather than true residuals. As a result, they should be standardised. Summing the standardised abnormal returns across securities, a normalised sum can be formed which is distributed unit normal for large N.[16] The PSR (Patell Standardised Residual) test explicitly recognises the possibility of different residual variances across securities, and weights the abnormal returns accordingly. It is based on the market model (because the estimated residuals come from OLS estimation of the market model). It is widely used for hypotheses testing in event-time approach. (Doukas & Travlos, 1988; MacKinlay, 1997).

2.2.2. Calendar-time Portfolio Approach

The calendar-time portfolio approach differs from conventional, market model event-time approach by estimating a multifactor (e.g. the Fama-French three factor) time-series

[16] Please see Appendix I in Chapter Three for details.

regression model for use in computing average abnormal returns. Some of the research takes Jensen's alpha as a measure of abnormal returns of portfolios (Eberhart, Maxwell, & Siddique, 2004; Ivkovich, Sialm, & Weisbenner, 2006).[17] Others apply calendar-time abnormal return (CTAR, differences between actual returns and the expected returns) as a proxy for abnormal returns (Byun & Rozeff, 2003; Mitchell & Stafford, 2000; Savor & Lu, 2009).[18]

We do not have an estimation period when evaluating performance using the calendar-time approach. For individual firms/stocks, the investigation period starts from the announcement/effective dates and ends three-five years afterwards. The calendar-time portfolio approach was first used by Jaffe (1974) to investigate the profitability of insider trading. It is currently popular in research on long-run performance (Byun & Rozeff, 2003; Mitchell & Stafford, 2000; Savor & Lu, 2009).

2.2.2.1. Benchmark Model

The Sharpe-Lintner CAPM (Lintner & John, 1965; Sharpe, 1964) suggests that the expected return on any asset *i* equals the risk-free interest rate, R_f, plus a risk premium. The risk premium is defined as the asset's market beta, β_{iM}, times the premium per unit of beta risk, $(R_m - R_f)$. This yield the time series regression:

(6) $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \varepsilon_{it}$,

where an intercept α_i is added, but whose expected value is zero for each asset.

[17] Jensen's alpha: A well-specified asset-pricing model assumes intercept is indistinguishable from zero in the time-series regressions (Dunne & Ndubizu, 1995; Harris & Ravenscraft, 1991; Lowinski, Schiereck, & Thomas, 2004; Mikkelson & Partch, 1986; Pettway et al., 1993). However, Jensen (Merton, 1973) argues that actually portfolio managers in mutual funds can increase returns on the portfolio through successful prediction of future security prices. In another word, the intercept (alpha) in assets pricing model can be different from zero.

[18] Please see Section 4.4.2. in Chapter Four for detailed description of CTAR.

Fama and French (1992; 1993) highlight the importance of two risk factors in asset pricing. They are the size factor (small minus big) and the book-to-market equity factor (high minus low). They build a three factor model (FF3FM) and argue that the model captures much of the variation in average return for portfolios formed on size, book-to-market equity and other price ratios that otherwise cause problems for the CAPM.

(7) $R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{mt} - R_{ft}) + \beta_{is} SMB_t + \beta_{ih} HML_t$

They also predict that the intercept "α_i" will be zero and this is supported by their empirical time-series regressions[19]. In other words, they find that overall abnormal returns are close to zero after we take market, firm size and book-to-market equity as risk adjustment factors.

2.2.2.2. Market Proxy Returns

Roll (1977) addresses that the market portfolio at the heart of CAPM is theoretically and empirically elusive. All the empirical tests use proxies, not the true market portfolio, and this is true for the FF3FM, too.

Moreover, market proxy becomes a far more serious problem in the global context. Most researchers apply world or regional indices contributed by Morgan Stanley. In theory, arbitrage activities should eliminate return differences, so that market returns will be identical across countries/areas. But in practice, this kind of trading is restricted because of regulations or information asymmetry, especially in emerging markets.

Cho, Eun, & Senbet (1986) provide an empirical investigation of the arbitrage pricing theory in an international setting. The results reject the hypothesis that international capital markets are integrated. Fama and French (1998) estimate an international version of FF3FM.

[19] Please see Page 36-27, Table 9a in Fama & French (1993) for evidence.

They find the FF3FM is much less reliable when applied to emerging markets compared to developed markets.

In conclusion, it is tricky to select the right market proxy in empirical tests when we apply the calendar-time portfolio approach to evaluate abnormal returns. Further, things get worse when emerging markets' share returns are included in the portfolio.

2.2.2.3. Clustering

The *t*-test statistic framework in calendar-time approach works properly in a random sample. However, if there are extreme firm, industry or calendar clustering in the M&A sample, cross-sectional dependence may cause misspecified inference (Lyon, Barber, & Tsai, 1999). Usually when overlapping returns are included in the sample, researchers adjust the variance-covariance matrix to incorporate clustering.

2.3. Empirical Literature on M&A Performance

A large literature examines M&A performance from a varity of perspectives. These include the performance of domestic or cross-border M&As, performance of M&As targets are in different nations, or in the U.S., or in other developed countries, or in emerging countries; short-term versus long-term performance of M&A; performance of bidders versus targets; performance measured by accounting method or stock market abnormal returns; M&A performance according to various transaction details, such as, different payment methods, different transaction forms, etc.

2.3.1. Domestic M&A Performance

2.3.1.1. M&A Performance in The U.S.

Most papers focus on US M&As. Berkovitch & Narayanan (1993) employ completed tender offers data (330 observations in total) from 1963 through 1988 in the U.S. to test motives for takeovers. They use the market model and 11-day cumulative abnormal returns

(CAR [-5,5]) to investigate announcement effects for both acquirers and targets. They find that, on average, takeovers yield positive CARs for both parties. When takeovers achieve positive gains, the total gain increases with competition for the target.

Heron & Lie (2002) investigate operating performance associated with U.S. takeovers during the period 1985-1997 (859 acquisitions in total). They use the market model and three-day CARs (CAR [-1,1]) to measure abnormal returns. They find no differences after takeovers. Neither do they find evidence that the method of payment conveys information about an acquirer's future operating performance.

Moeller, Schlingemann, & Stulz (2005) compare acquiring firms' returns in three time periods, 1980-1990, 1991-2001, 1998-2001 in the U.S. market. They use three-day CARs (CAR [-1,1]) to measure M&A announcement effects. They find that the acquiring firm loses value in the announcement period, and that the losses of bidders exceed the gains of targets. Further, firms announcing acquisitions with large dollar losses perform poorly afterwards.

Masulis, Wang, & Xie (2007) use a sample of 3,333 completed acquisitions during the period between 1990 and 2003 in U.S.. They examine five-day CARs (CAR [-2,2]) generated from the market model and find that acquirers with more anti-takeover provisions experience significantly lower announcement-period abnormal returns. Acquirers operating in more competitive industries experience higher announcement abnormal returns. Higher CARs are generated when the positions of CEO and the chairman of the board are separate.

Loughran & Vijh (1997) use acquisitions during 1970-1989 in the U.S. to investigate long-term M&A performance (405 observations in total). Fama & French's size and book to market effects are included in their five year-long window for buy-and-hold abnormal return measurement. They find significant negative excess returns of -25% in the five-year period following the acquisition, whereas cash tender offers earn significantly positive excess returns of 61.7%.

Rau & Vermaelen (1998) test acquiring firms' long-term performance (3 years following the completion date) from January 1980 to December 1991 in the U.S. (3169 mergers and 348 tender offers in total). Monthly ARs and CARs are measured relative to a size and book-to-market based benchmark. Bidders in mergers underperform, while bidders in tender offers outperform in the three years after the acquisition. However, the long-term underperformance of acquiring firms is predominantly caused by the poor post-acquisition performance of low book-to-market firms.

2.3.1.2. M&A in Other Developed Countries

Firth (1997) uses New Zealand M&A data (162 observations in total) during the period 1970-1987. The market model is employed and monthly CAR40s are measured. The results indicate that target firm shareholders gain from the takeover process, but that the acquiring companies suffer losses. The losses to acquirers are lower when payment is in cash. Acquirers who make uncontested bids tend to experience more negative returns.

Sudarsanam & Mahate (2003) study completed U.K. M&As with transaction value above £10 million over the time period 1983-1995 (519 observations). Four benchmark models are employed: mean-adjusted model, market-adjusted model, size-adjusted model and market model. Daily buy and hold abnormal returns (BHARs), covering the day-spans (-1,1), (2,40), (41,750) are measured. They find that acquirers experience BHARs in the region of -1.4% at the time of the announcement and an average of -15% over the three-year, post-acquisition period.

Andre et al. (2004) focus on long-term M&A performance for Canadian firms with transaction values greater than US$10 million over the period 1980-2000 (267 observations). They employ the Fama & French Three-factor model and mean calendar-time abnormal return methodology to investigate 12, 24, and 36-monthly returns. They conclude that Canadian acquirers significantly underperformed over the three-year, post-event period.

2.3.1.3. M&A Performance in Emerging Economies

Li & Chen (2002) use event study methodology to test 349 M&A events in China during 1999 to 2000. The authors find that M&As generate significant wealth effects for acquirers instead of targets. Zhang (2003) investigates 1216 Chinese M&As from 1993 to 2002. On the contrary, he finds improved performance for the targets, not the acquirers. Insignificant performance is found when the performance of targets and acquirers are combined.

2.3.1.4. Other M&A Performance Literature

Jensen & Ruback (1983) review much of the scientific literature before 1983 and conclude that the targets of successful tender offers and mergers earn significantly positive abnormal returns on the announcement of offers, and through the completion of offers. Targets of unsuccessful tender offers earn significantly positive abnormal returns on the offer announcement and through the realization of the failure. Targets of unsuccessful mergers lose all positive returns earned in the offer announcement period by the time failure of the offer becomes known. However, with respect to acquirers, both successful and unsuccessful bidders achieve nonnegative abnormal returns. Takeover gains do not come from the acquisition of market power, but from some source of efficiency that also appears to be available to rival firms in the industry.

Jensen (1986) develops the “free cash flow” theory. He argues that mergers and takeovers are more likely to destroy, rather than to create value, especially for bidders. Takeovers financed with cash and debts generate larger benefits than those accomplished through the exchange of stock.

Healy (1992) uses accounting data from the 50 largest mergers in the U.S. in the period 1979 to 1983 to evaluate M&A performance. He finds a significant increase in post-merger cash flow. Merged firms have significant improvements in operating cash flow return at the time of merger announcements.

In summary, empirical studies on domestic M&A performance show conflicting results. However, most of the papers in this subsection support the idea that acquiring firms suffer losses in domestic M&A events. M&As achieve nonnegative abnormal returns when returns from acquirers and targets are combined, usually the shareholders of the target firms gain more than those of the acquiring firms.

2.3.2. Cross-border M&A Performance

Studies on cross-border M&A, however, have quite different results.

2.3.2.1. Cross-border M&A Performance in The US

Doukas & Travlos (1988) study international acquisitions from 1975 to 1983 where American firms are either the acquirers or the targets. The market model is employed to generate daily ARs over days (-5,5); and the daily mean difference of abnormal returns is measured. The authors divide their original sample into three homogeneous subsamples according to the degree of international exposure (already operating in the target firm's country, not operating in the target firm's country, and going abroad for the first time). The result shows that shareholders of MNEs not already operating in the target firm's country reap the greatest benefits from international acquisitions when their firms expand into a new industry and geographic market. Shareholders of MNEs operating in the target firm's country experience insignificantly negative abnormal returns. Domestic firms expanding internationally for the first time experience insignificantly positive valuation effects.

Harris & Ravenscraft (1991) examine 1273 U.S. firms acquired by foreigners during the period 1970-1987. The market model is employed to generate daily ARs, CAR (-3,1), and CAR (-20,4). Most of the takeovers achieve positive abnormal returns. Harris and Ravenscraft argue that the targets of foreign buyers have significantly higher wealth gains than the targets of U.S. firms. Also, cross-border takeovers are more frequent in research and development-intensive industries. In addition, the M&A effect is positively related to the weakness of the U.S. dollar.

Morck & Yeung (1992) examine 322 foreign acquisitions by U.S. corporations between 1978-1988. They find that the mean abnormal return is 0.29%, significantly above zero. Firms with information-based assets experience a significantly positive stock price reaction upon announcing a foreign acquisition, while firms apparently lacking such assets experience, at best, zero abnormal returns. The authors attribute their findings to internalization theory, specifically, that firms with technology-related intangible assets experience high abnormal returns.[20]

Pettway, Sicherman, & Spiess (1993) investigate Japanese acquirers having U.S. targets from October 1981 to September 1991. Their data consist of fifty-three Japanese acquirers and forty U.S. asset sales. The authors employ the market model and use daily cumulative prediction errors (CPEs) to measure announcement wealth impacts. They find both Japanese buyers and U.S. sellers achieve significant wealth effects at the time of the announcement relative to domestic Japanese M&As. In the case of U.S. assets purchases,

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[20] Internalization theory was first developed by Buckley & Casson (1976). It centers on the fact that a MNE carries out many activities that are interdependent and related through flows of intermediate products. (These include materials, components and semi-finished goods, which are sometimes in tangible forms. More often they are in intangible forms and knowledge-based, such as patents, engineering expertise, management and marketing skills, and quality control). Since markets for intermediate products are difficult to organize, these transactions can be handled more efficiently within the firm by an internal hierarchy rather than by an external market. The creation of internal markets brings these activities under the direct ownership and control of the firm.

Japanese acquirers also gain significantly positive CPEs at the time of the announcement. The authors' results are consistent with the existence of imperfections in globally integrated capital markets.

Dunne & Ndubizu (1995) employ the market model on daily data to investigate ninety-five acquisitions of U.S. target firms by foreign bidders in the period 1983-1988. Average standardized cumulative abnormal returns (ASCAR) are positive for different subgroups during the event window days (-20,20). The results show that acquirers who write off goodwill against a reserve account provide significantly greater abnormal returns to target shareholders on the acquisition announcement date than those acquirers who amortize goodwill against income. Foreign acquirers already operating in the U.S. transfer more wealth to the target than those who are expanding into the U.S. market for the first time.

Doukas & Lang (2003) use 156 greenfield investments (having $3 million of investment project value or more) of U.S. firms during 1980-1992 and supervise FDI performance with respect to geographic diversification. The authors estimate CARs and by-and hold returns (BHARs). They get significantly negative CAR (-1,0). When the sample is broken down into core-related and non-core related investments, core-related investment achieves positive 0.24% CAR(-1,0) while non-core related investments suffer -0.38% CAR(-1,0). The same story happens when 2-year and 3-year BHARs are employed in the study. It is obvious that unrelated FDI results in a negative effect and deteriorating performance.

2.3.2.2. Cross-border M&A Performance in Other Developed Economies

Gugler, Mueller, Yurtoglu, & Zulehner (2002) focus on the effects of mergers around the world (69,605 observations in total) during the period 1981 to 1998. They use profitability and sales to measure the effects of mergers and find that 57% achieve positive profits and 51.5% generate positive sales one year after the merger. When they extend their horizon to five years after the merger, they find that 54.8% have positive profit and 44.6%, positive sales. The authors also employ control-firm analysis to compare the performance of the merging firms with nonmerging firms. The results show significant increases in profit, but reduction in the sales of the merging firms on average. The authors' results reveal no major differences between domestic and cross-border mergers.

Andre et al. (2004) focus on Canadian long-term M&A performance with a sample of 267 events above USD 10 million during 1980-2000. They employ the Fama and French Three-factor model, and alpha and mean calendar-time abnormal return (MCTAR) methods to investigate 12, 24, and 36-monthly returns. They conclude that Canadian acquirers significantly underperform over the three-year post-event period. They argue that cross-border deals involving Canadian acquirers perform poorly in the long run.

Francoeur & Montreal (2005) also employ the Fama and French three-factor model in their research. A control-firm event approach and calendar-time approach are used to investigate long-term performance of Canadian acquirers in cross-border M&As. They use 847 cross-border M&A events in the year 1990-2000 and find that firms subsequently outperform the level of return generated by their peers within their main industrial sector. They find that firms possessing high levels of R&D and a strong combination of R&D and intangibles are necessary conditions for achieving better long-term performance.

Lowinski, Schiereck, & Thomas (2004) analyze wealth effects of 114 domestic and international acquisitions announced by Swiss corporations between 1990 and 2001. They apply the market model and find significant positive daily CARs for cross-border acquisitions but no difference between national and cross-border M&A announcement effects. The authors also find that the expenses of investment bank advice might outweigh the potential benefits.

2.3.2.3. Cross-border M&A Performance in Emerging Economies

Aybar and Ficici (2009) examine 433 merger and acquisitions associated with 58 Emerging Market Multinational enterprises (EMMs) during the sample period 1991-2004. On average, cross-border expansions do not create value. They find that more than half of the transactions diminished firm value. The cross sectional regression results show that target size, ownership structure of the target, structure of the bidder (diversified vs non-diversified) positively affect the bidder value. High-tech nature of the bidder and related OMAs negatively affect the bidder value.

Pradhan and Abraham (2005) examine the patterns and motivations behind overseas M&As by Indian enterprises. They find that a large majority of overseas M&As originate within the services sector, led by the software industry. The overwhelming number of cases are directed towards developed countries. The main motivations of Indian firms' overseas acquisitions are to access international markets, acquire firm-specific assets like technology and human skills, exploit operational synergies, overcome constraints from a limited home market, and gain sufficient size strength to survive in an increasingly competitive business environment. In the manufacturing sector, overseas acquirers tend to be large-sized and research-intensive; while they are older, large-sized and export-oriented in the case of the software sector.

Kim (2003) studied 256 Outward Foreign Direct Investment (OFDI) cases of South Korean firms during the period January 1992 to June 1997 where the investment exceeds \$500,000. Using daily AARs and CARs, they conclude that OFDI announcements by acquirers increase shareholder value. In contract, cross-border investments do not increase shareholder wealth for the 30 largest chaebol-affiliates. Shareholder wealth losses are greater when corporate ownership is concentrated.

Wang & Wang (2006) employ accounting data (ROA, ROE and sales growth) to investigate 27 Chinese firms' performance after they completed outbound M&As in developed countries such as the U.S. and countries in the E.U. They find a decrease in the three accounting measures in the following two years.

2.3.2.4. Cross-border M&A Performance in Specific Industries

Amihud, Delong, & Saunders (2002) examined 214 cross-border banking mergers announced between 1985 and 1998 throughout the world. With daily data and a (-10,1) event window, the authors find that CARs for acquirers are negative (approximately 1%) and significant. They find a positive, albeit weak, increase in the total risk. They conclude that the growth of cross-border banking appears to pose limited systemic risk to the stability and solvency of the international banking system.

Boubakri et al. (2008) examine the long run performance of M&A transactions in the U.S. property-liability insurance industry. With a sample of 177 transactions, of which 30 are cross-border, the authors find that M&As in this industry create value in the long-run (positive BHARs after 3 years). In addition, tender offers appear to be more profitable than mergers. Further, positive returns are significantly higher for frequent acquirers and in countries where investor protection is weaker. The study also reports that internal corporate governance mechanisms such as board independence and CEO share ownership are contributors to the long run positive performance of bidders.

A paper titled *The Wealth Effect of Cross-border Merger and Acquisitions in The Chinese Financial Sector* (2008) investigates 37 cross-border M&A transactions in the Chinese financial sector (foreign acquirers and Chinese targets) during the period 1990-

2005.[21] Employing the market model, the paper shows that both experienced foreign bidders and Chinese targets obtain significant positive wealth gains during the event, while inexperienced foreign bidders suffer losses. Foreign bidders with Chinese banking targets experience positive wealth gains, while they suffer losses with Chinese non-banking targets. Moreover, the wealth gains to foreign bidders are positively related to exchange rate volatility and to the size, business scope and geographic location of the foreign bidders. Bidders listed in Hong Kong experienced better wealth gains than those listed in mainland China.

2.3.3. Discussion

Differences in factor endowments between acquirers and targets and uncertain economic environments make it difficult for acquirers to integrate international resources, contributing to higher investment risks. It is argued that firms should invest abroad only after they have attained a sufficient level of development, and achieved a competitive (absolute or comparative) advantage in their domestic markets. Due to international market imperfections, it is possible for firms involved in cross-border M&As to achieve larger abnormal returns than domestic ones. In contrast to the results from the domestic M&A performance research, cross-border M&A performance studies tend to find positive gains, or at least zero abnormal returns, for acquiring firms. They also find that acquiring firms gain more than targets unless a host country's environment forces them to transfer more wealth to their targets.

Because of imperfect information and separate international stock markets (different benchmarks), it is difficult to collect the completed data required to estimate the performance of both acquirers and targets. Therefore, a number of the papers focus on cross-border M&A performance in one market, for example, in the US market from both an acquirer and a target perspective. More papers focus on acquirers only or targets only. The financial sector is

[21] Author unknown, but the paper is available at www.ccfr.org.cn/cicf2007/download.php?paper .

considered as an industry with a special characteristic, thus it is usually investigated separately (Altunbarş, Molyneux, & Thornton, 1997; Amihud et al., 2002; Boubakri et al., 2008; Catarina, Joseph, & Richard, 2007; Marc, Dirk, & Markus, 2006; The Wealth Effect of Cross-Border Mergers and Acquisitions in the Chinese Financial Sector ", 2008).

Researchers employ different methodologies to evaluate M&A performance (event study, accounting method or survey). Event studies are the most common. However, some authors use surveys to collect data for long-term cross-border M&As or greenfield investment performance. Most papers focus on M&A performance in developed countries, for example, the U.S., the U.K., and Canada. Studies focusing on overseas M&As (a subset of OFDI) in emerging economies or developing countries are rare. China has attracted attention primarily as an important M&A host country, rather than as the home country of acquirers. In the case of Chinese cross-border M&As, papers tend to be more about M&A motives, M&A strategies, fit and the relationship between M&A and technology development. There have been very few empirical papers on Chinese outbound M&A performance. Qualitative rather than quantitative studies have been employed in investigating determinants of Chinese outbound M&A performance.

2.4. Performance Determinants

Generally speaking, the performance of OMAs is jointly decided by M&A transaction details, acquirers' endowments and location of the targets. In emerging markets, the government's promotion policies in OMAs play an important role in their performance.[22]

Firstly, transaction details are regarded one of the key factors of M&A performance. Top managers suffer from information asymmetry in M&A transactions. M&As end up with unexpected outcomes because of improper asset pricing, miscalculation of overall transaction

[22] Please see Chapter Three for details.

value, and employing incorrect forms of acquisition or payment method. Occasionally, weaker corporate governance structure leads to top managers' irrational decision-making, causing acquirers to pay too much for the deals (Hymer, 1960; Vernon, 1966).

Secondly, bidder's endowment is another consideration in OMA performance. Small firms or value firms have consistently superior M&A performance. Acquirer's ownership structure is another factor related to OMA performance. In the emerging markets literature, acquirers that cross-listed signal informational transparency and experienced international operations. Thus, they are expected to perform better in OMAs.

Thirdly, target location is one of the critical elements of OMA performance. When MNEs invest overseas, the host country's institutional environment contributes to OMA performance. Investor protections vary across different host countries. Favourable foreign direct investment (FDI) policies and regulations, financial transparency, the level of economic development and political stability are supportive factors for OMA performance. Foreign exchange rate volatility and culture differences also affect OMA performance.

2.4.1. Transaction Details and M&A Performance

M&A performance varies with different M&A transaction characteristics. In this subsection we will cover findings that relate transaction characteristics to M&A performance. Key transaction characteristics are methods of payment (cash or stock payment), form of acquisition (tender offer or merger), whether the acquirer and target industries are related, the role of professional advisors, and the number of bidders.

2.4.1.1. Method of Payment

The method of payment hypothesis (first mentioned in Jensen and Meckling, 1976) implies that top managers employ cash as their M&A payment only if they have enough cash flow and foresee bright prospects for post-merger performance. As an alternative to cash payment, acquirers can exchange stocks with targets to share risk, making the target shareholders equity-holders in the acquirer. In other words, if acquirers are sure that an M&A will be profitable and do not want to share the extra gain with others, they will choose cash payment. Thus the method of payment turns out to be a signal to outside investors as to whether a given M&A will be profitable. Many empirical results support the method of payment hypothesis (Harford, Mansi, & Maxwell, 2008).

2.4.1.2. Forms of Acquisition

The distinction between friendly and hostile takeovers is examined by many researchers (Firth, 1997; Jensen, 1986; Loughran & Vijh, 1997; Sudarsanam & Mahate, 2003). Hostile takeovers are more costly and often result in failure because the managers of targets find ways to defence themselves, for example, a poison pill, or white knight manoeuvres.[23][24] On the other hand, a friendly takeover implies that managers of targets are willing to cooperate with the bidders during the negotiation and post-merger integration. However, it also may indicate weakness. Targets may lack competitive power in the market and need a helping

[23] Poison pills (Or called a shareholder rights plan) is a kind of defensive tactic used by a corporation's board of directors against a takeover. It involves a scheme whereby shareholders will have the right to buy more shares at a discount, if one shareholder buys a certain percentage of the company's shares. The plan could be triggered, for instance, when any one shareholder buys up 20% of the company's capital, at which point every other shareholder (except the one who already possesses 20%) will have the right to buy a new issue of shares at a discount. The plan is issued by the board as an "option" or a "warrant" attached to existing shares, and can only be revoked at the discretion of the board of directors. The point is that the shareholder who could potentially reach the 20% threshold will be a takeover bidder. If every other shareholder will be able to buy more shares at a discount, that will mean the bidder's interest will be diluted, and the cost of the bid will rise substantially. If the bidder knows that this will happen, the bidder will not attempt to take the corporation over without the board's approval. They will negotiate with the board so that the plan is revoked.

[24] There are two types of white knight. The first type, the white knight, refers to the friendly acquirer of a target firm in a hostile takeover attempt by another firm. The intention of the acquisition is to circumvent the takeover of the object of interest by a third, unfriendly entity, which is perceived to be less favorable. The knight might defeat the undesirable entity by offering a higher and more enticing bid, or strike a favorable deal with the management of the object of acquisition. The second type refers to the acquirer of a struggling firm that may not necessarily be under threat by a hostile firm. The financial standing of the struggling firm could prevent any other entity being interested in an acquisition. The firm may already have huge debts to pay to its creditors, or worse, may already be bankrupt. In such a case, the knight, under huge risk, acquires the firm that is in crisis. After acquisition, the knight then rebuilds the firm, or integrates it into itself.

hand to survive. Given this background, a successful tender offer usually indicates a more profitable future than a friendly merger.

2.4.1.3. Industry Relatedness

Firms in related industries usually possess similar technologies and managerial structures, which lead to better communication and successful post-merger integration. Firms in related industries can also potentially share firm-specific resources, such as distribution networks and human resources. Further, top managers often have little knowledge about operating firms in unrelated industries. This leads to faulty decision-making and misunderstandings between acquirers and targets. These are obstacles to post-merger synergy. Therefore, rational investors will make their investment decisions according to the outcome of M&A relatedness, which in turn, will set the stock price (Boubakri et al., 2008; Eckbo, Giammarino, & Heinke, 1990; Jensen & Meckling, 1976; Rau & Vermaelen, 1998).

2.4.1.4. Professional Advisers

Bidders employ professional advisors in M&A transactions to gain a better knowledge of the targets and thereby make more informed M&A decisions (Doukas & Lang, 2003; Dunne & Ndubizu, 1995; Harris & Ravenscraft, 1991; Hopkins, 1999). Professional advisors also play an important role in facilitating the transaction and with post-merger integration. They are supposed to be better informed and equipped with M&A knowledge, which are crucial for a M&A to be successful. These services don't come cheap. Bidders pay large sums of money as fees for their direction. Even with professional advisors, there are no guarantees that a deal will be successful.

The number of bidders is an indicator of the potential value of a target. If it is believed in the market that an acquirer might achieve a positive abnormal return from an M&A, which means there are opportunities for excess profits, more bidders will join in the competition (Lowinski et al., 2004).

2.4.2. Acquirers' Endowment and M&A Performance

Bidders' endowment relates to ownership advantage and their capability of exploiting benefits after the OMA. Associated variables include firm size, book-to-market equity, ownership structure, R&D intensity and OFDI experience of the acquirers.

2.4.2.1. Firm Size and Leverage Level

Banz (1981) finds that, on average, smaller firms have higher risk adjusted returns than larger firms. The estimated effect is nonlinear. The main effect occurs for very small firms, while there is little difference in returns between average-sized and large firms. Fama and French (1992) also find a size effect in their time series regression of CAPM. Asset pricing models perform much better when size and leverage factors (SMB and HML respectively) are included. Gugler et al. (2002) argue that M&As between small firms increase efficiency by creating economies of scale and scope while mergers between large firms increase market power.

Many papers support the view that value firms tend to outperform glamour firms (Rau & Vermaelen, 1998; Sudarsanam & Mahate, 2003).[25] Chan, Hamao, & Lakonishok (1991) find a significant positive relationship between book-to-market ratio and expected returns in the Japanese share market. Using U.S. data, Fama and French (1992; 1993) find a positive relationship between book-to-market equity and expected returns.

[25] "Value firms" are high book-to-market ratio firms and "glamour firms" are low book-to-market ratio firms in this study.

2.4.2.2. Ownership Structure

Evidence from developed markets indicates that family or CEO share ownership is positively related to firm performance (Ben-Amar & Andre, 2006; Boubakri et al., 2008; Porta, Lopez-de-Silanes, & Shleifer, 1999).

Morck et al. (2008) study Chinese OMAs and find that China's outward foreign direct investment was mostly conducted by state-owned enterprises (SOEs). Wei, Xie, & Zhang (2005) and Hess, Gunasekarage, & Hovey (2008) both apply Tobin's Q as firm's performance and exam its relationship with Chinese government ownership. Wei, Xie, & Zhang (2005) find that Chinese state and institutional shares are significantly, negatively related to firm performance. In contrast, Hess, Gunasekarage, & Hovey (2008) find that firms with combined state ownership at levels above approximately 35% are superior performers. They also find evidence that firms owned by large private shareholders tend to underperform.

Xu & Wang (1999) and Sun, Tong, & Tong (2002) use accounting data, market-to-book ratio (MBR), as a measure of firms' performance. Xu & Wang (1999) report a positive and significant correlation between ownership concentration and profitability. Moreover, Chinese firms' profitability is positively correlated with the fraction of institutional shares, but either negatively or uncorrelated with the fraction of state shares and privately-owned tradable shares. On the other hand, Sun, Tong, & Tong (2002), report that Chinese government ownership and firm performance are positively, but nonlinearly, related. Yet, the relationship is nonlinear. When an SOE begins selling a small portion of shares to the public, the firm's performance improves. Beyond a certain level, increased selling of government shares to the public is correlated with poorer firm performance. They argue that the government plays some important and supportive roles for SOEs.

2.4.2.3. R&D Intensity

In accordance with internalization theory, the relationship between R&D and cross-border M&A performance has been explored by a number of researchers. Harris & Ravenscraft (1991) find that cross-border takeovers are more frequent in R&D-intensive industries than in domestic ones. Morck & Yeung (1992) find firms with information-based assets are likely to experience a significantly positive stock price reaction upon announcing a foreign acquisition. By contrast, firms without such assets experience, at best, zero, abnormal returns.

Francoeur & Montreal (2005) suggest in their paper that acquirers engaging in cross-border M&As are able to realize efficiency gains and create value for their shareholders under certain condition such as possessing high levels of R&D and a strong combination of R&D and intangibles. Cross-border M&As create value for the acquirers because they can bring their expertise and know-how into the international market.

2.4.2.4. OFDI Experience

With respect to the OFDI experience, Dunne & Ndubizu (1995) point out that acquirers with previous experience in the U.S. market transfer more wealth to target shareholders than those entering the U.S. market for the first time. Uhlenbruck (2004) use 170 acquisitions in Central and Eastern Europe and find evidence that MNEs' pre-acquisition experience in host country are positively related to the growth of acquired foreign subsidiaries.

2.4.3. Target Location and OMA Performance

The location of the target firm becomes an important issue in cross-border M&A deals. Different foreign locations will have different levels of country risk, cultural distance, exchange rate exposure, and different economic growth rates. These all relate to M&A performance.

Doukas & Lang (2003) present evidence that geographic diversification increases shareholder value and improves long-term performance. Child et al. (2003) shows that environment determines business performance (natural selection). They examine business environment variables (market attractiveness, intensity of competition, environmental unpredictability and resource availability) and institutional environment variables (legal support, importance of guanxi, official intervention and arbitrariness of officials) in their study. The results show that Hong Kong firms operating under more favourable external circumstances in China have a better cross-border M&A performance.

2.4.3.1. Country Risk

Country risk is one of the most important elements in creating differences in cross-border M&A performance. Generally speaking, developed countries have lower country risk than developing countries. Countries with dissimilar social systems have different degrees of transparency. Under democratic political systems, a party's reign is supervised by opposition parties, which breeds more transparency in the political environment. In autocratic countries, at the opposite end of the spectrum, expropriation occasionally happens, which is considered to be a foreign direct investment (FDI) risk by investors. At the same time, corruption is a by-product of the centralization of power, which acts as a negative investment incentive to foreign investors as well.

2.4.3.2. Cultural Distance

Cultural distance is another consideration. There are two levels of culture distance. Firstly, culture is a "common psychological process". Nations that cannot be grouped by a shared language, set of religions or customs are deemed to be different in culture. Similarly, at the company level, corporate culture develops in tandem with the firm and becomes one of its intangible assets. Staff in the same corporation gradually settle on a shared way of thinking as to how things should be done, which helps with cooperation in teamwork and communication.

On the other hand, culture differences between corporations will block communication and raise transaction costs (Hofstede, 1980; Kogut & Singh, 1988; Morosini, Shane, & Singh, 1998). It is one of the crucial elements that influence firms' cross-border M&A strategy. Some researchers have found that cultural distance has a negative effect on post-merger performance (Li, Lam, & Qian, 2001).

Others, however, obtain the opposite result. Morosini et al. (1998) examine 52 cross-border M&As in 1987-1992 and they find a positive association between national cultural distance and cross-border acquisition performance. Larsson & Finkelstein (1999) also argue that cultural distance improves post-merger performance, and that cross-border M&As lead to higher potential firm value and lower staff attrition because of mutual complementarity of resources. Cultural distance is thus deemed to be a "soft" resource of comparative advantage.

2.4.3.3. Foreign Exchange Rate

Foreign exchange rate has little effect on domestic M&A performance. However, it does matter for bidders and targets in cross-border M&A transactions. Furthermore, the relationship between foreign exchange rate and OMA performance has multiple dimensions.

The first is transaction exposure. When bidders and targets successfully finish their negotiation, the exchange rate variation between two or more currencies will decide the final deal value in their local currencies. If currency in the acquirer's home country has depreciated, it raises the transaction costs for the acquirer. Alternatively, if the currency in target's country has depreciated, the bidders will pay less for the same deal.

The second aspect is operating exposure. This is also called economic exposure with respect to cross-border M&As. Subsidiaries of multinational enterprises in different host countries will face exchange rate exposure in their ongoing business with their overseas parents. For example, when they import work-in-process inventories from the parent corporation, exchange rate fluctuation will affect the deal value, which will have a downstream effect on costs, future sales volume and price. Multinational enterprises with international investment experience can eliminate this exposure in the long run in a number of ways. For instance, they can use re-invoicing centres to cluster exchange rate exposure in different affiliates and employ hedging (with financial derivatives) to manage the distribution of expected cash flow.

The third aspect is accounting exposure. This relates to the potential for accounting-derived changes in owner's equity to occur because of the need to translate foreign currency financial statements of foreign affiliates into a single reporting currency for worldwide-consolidated financial statements. This exposure shows on the balance sheet and has no actual influence on operations.

Cushman (1985) argues that random fluctuations in the real exchange rate lead to a range of risk and expectation effects on FDI. His empirical study shows that increases in the current real value of foreign exchange are associated with significant reductions in U.S. direct investment.

Froot & Stein (1991) present a model to examine the connection between exchange rates and foreign direct investment. They show a depreciated currency can give foreigners an edge in buying control of productive corporate assets. In another word, the relative wealthier buyers find it easier to acquire foreign assets. Cebenoyan, Papaioannou, & Travlos (1992) provide significant evidence that exchange rate, tax regimes and technology influence foreign takeovers. Foreign takeover competition offer the most powerful and consistent explanation of the difference in wealth gains.

Dewenter (1995) employs data on foreign acquisitions of US targets during 1975-1989 to explore the relationship between the value of the dollar and the flow and prices of cross-border acquisitions. 3036 transactions involving at least a 10% equity investment and $1 million in value are investigated. The result shows that the exchange rate variable clearly impacts corporate wealth.

This finding is in stark contrast to that of Pettway et al. (1993) who find that the magnitude of the gains depend more on the relative market power among the buyers and sellers and on the nature of the assets being purchased, rather than on variation in exchange rates.

2.4.4. Discussion

As the previous survey indicates, there are many determinants involved in cross-border M&A performance. The complexity of their interrelationships makes it difficult to select representative independent variables that are not highly correlated with each other.

The task is further complicated by the fact that there are there are three levels of determinants (M&A transaction characteristics, targets' location and bidders' endowment), with multiple variables within each level.

Another consideration is that we need to combine the motives of Chinese overseas M&As with the determinants of the M&A performance. Consider the case of Chinese overseas M&As which are upstream OFDI (i.e, the acquirer is from a developing country, while the target is from a developed country). M&As that fall into the upstream OFDI category may be much less likely to achieve positive abnormal returns. However, top managers of Chinese MNEs or the government regard this category of M&A as a strategic investment that gives access to strategic resources.

2.5 Conclusion

This chapter reviews the literature related to my thesis — "A Study of Chinese Overseas M&A:1994-2009". We follow a framework of four sections: Motives, Methodology, Performance and Determinants.

The motive section provides the possible answers for the recent Chinese OMA wave. The methodology section introduces event study procedures and asset pricing arguments related to an evaluation of OMA performance. The performance section reports general empirical results on domestic/ cross-border M&A performance among industries in developed/ emerging markets. The determinants section concludes by relating transaction details, bidders' endowment and targets' location variables to OMA performance.

When it comes to an analysis of Chinese OMAs, the important role played by Chinese governments and state-owned enterprises needs always to be kept in mind. With respect to firm-specific level motives, these relate to resources and strategic asset seeking.

Because this thesis is based on an empirical analysis of short and long-run performance and determinants, we review the literatures on the event-time and calendar-time approaches, and asset pricing benchmark models (the market model and the Fama French Three Factor Model). We will apply these in evaluating Chinese short-run and long-run OMA performance respectively.

Although efficiency market theory implies short and long-run M&A performance to be identical, empirical analyses frequently end up with conflicting results across developed/emerging markets, and industries. Researchers try to explain these market anomalies with various arguments. They highlight OMA performance determinants in three aspects: transaction details, bidders' endowment and targets' location. Finance researchers focus on firm-specific factors; for example, payment method, form of acquisition, and agency issues in corporate governance. International economists emphasize policy, country risk, exchange rate variation and cultural differences. Both finance and economic literatures pay attention to bidders' endowment in OMA. However, finance papers investigate the relationship between firm size/leverage level with OMA performance, while international economists look at acquirers' ownership and internalization advantages and their OMA performance.

There are a few empirical literatures on emerging OMA performance. Papers on Chinese OMAs, however, have shown more interest in analysing strategic motives and the determinants of OMA itself, instead of carefully analysing performance.

China still maintains a communist system and pursues a "dual track" approach. "Market track" and "planned track" are two legs in the "dual-track" approach of the Chinese economic system. Firm-specific profitability is one of the essential conditions in order to achieve national goals. Therefore, shareholders' interests in OMAs are necessarily components of government strategy, especially in the long-run. This motivates our research to study Chinese OMA performance and its determinants from a firm-specific perspective.

Chapter Three Chinese Overseas M&A Performance and Go Global Policy

This chapter provides a thorough analysis of Chinese outbound merger and acquisitions (OMAs) over the period 1994-2009. We use event-time approach to analyze the performance of OMAs by Chinese acquiring firms. With a sample of 157 OMA events, we find that on average, Chinese OMAs produced positive abnormal returns. However, markets responded less favorably after the "Go Global" strategy of the Chinese government.

We hypothesize three reasons for this: (i) The Demand and Supply Hypothesis: The deregulation of overseas investment after the "Go Global" era increased the number of deals, which decreased the inframarginal rents associated with those deals. (ii) The Government Capitalization Hypothesis: "Go Global" re-directed investment towards industries having national strategic value but diminished profit value of shareholders. (iii) The Hubris and Herding Hypothesis: hubris and herding behavior of top managers misled decision-making in OMAs. The subsequent expansion of OMAs under "Go Global" resulted in Chinese firms pursuing less attractive targets, on average. We find no evidence to support the latter two hypotheses. Thus, to whatever extent strategic or top managers' interests may motivate China's "Go Global" policy, it does not appear that their pursuit has come at the expense of shareholder's wealth.

3.1. Introduction

The exceptional performance of the Chinese economy has been the subject of many academic analyses. Over the last fifteen years, Chinese GDP growth has averaged approximately 10 percent. Associated with this growth has been a dramatic increase in the Chinese trade surplus and foreign exchange reserves.[26] "Go Global" is the banner name of a national policy encouraging outward investment by Chinese firms. It was initially introduced in 1999, but has evolved over time to represent a conglomerate of individual policies. Apart from reducing appreciation pressure of Chinese RMB, the "Go Global" policy addresses concerns of sufficient resources for sustainable development. Moreover, it motivates Chinese firms to modernize their business via the appropriation of foreign technology and the assimilation of modern business practices.

By one measure, Chinese overseas mergers and acquisitions (OMAs) activity rose from US$307 million in 1994 to over US$26.5 billion in 2008.[27] This increase in OMAs sustained itself even after the world financial crisis. Clearly, the Chinese OMA wave in 2002-2009 is an important part of government Go Global policy.

This raises a number of questions:

1. Do Chinese OMAs create value for shareholders?
2. Does the Go Global policy damage shareholders' wealth?

Surprisingly little is known about the performance of Chinese OMAs. To the best of our knowledge, the only academic study that measures stock market reactions to Chinese OMA announcements is Chen and Young (2009). They examine 39 deals and find a negative but

[26] Over the period 1994 to 2007, Chinese foreign exchange reserves increased from US$52 billion to over US$15 trillion (National Bureau of Statistics of China, 1996, 2008).
[27] World Investment Report, United Nations, 2006, 2008.

statistically insignificant market response to OMA announcements on the (-1,0) window. They also report a negative relationship between government ownership and cumulative abnormal returns.

Among the non-academic literature, Hemerling and Michaelis (2006) study 16 deals and find that "relative total shareholder returns" around the announcement day were positive in 56% of deals.[28] Luedi (2008) analyzes 56 deals over the period 1995-2007 and reports that Chinese acquirers "overpaid" for foreign assets in 55 percent of deals, as measured by the change in share prices around the announcement day.[29] Other studies summarize various features of Chinese OMAs, such as location of target firms, characteristics of target industries, and motivations underlying foreign acquisitions (Deng, 2007; Liao, 2006; Rui & Yip, 2008). However, these rely largely on summaries of aggregate activity, and case studies of a few firms without any formal analyses. This study provides the most comprehensive analysis of Chinese OMAs to date, analyzing a total of 157 deals made over the years 1994-2009.

In this chapter, we first employ event study methodology to evaluate the stock market performance of Chinese acquirers. We next assess whether the national strategic goals of this policy have come at the expense of shareholders of Chinese, acquiring firms.

The results show that Chinese outbound M&As (1994-2009) have achieved significant positive abnormal returns in total, which indicate a successful "globalization" strategy for Chinese giants.

However, Chinese OMAs after "Go Global" underperformed compared to before the policy, though the differences are not significant. It might be the outcome of the interaction of international supply and demand in OMA targets. Or motivation conflict between

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[28] "Relative total shareholder return" is defined as "Total shareholder return" minus "Return of stock market index of the local market" as measured during the (-5, 5) window.

[29] Luedi (2008) defines "overpaid" as a negative share price movement in the (-2, 2) window.

shareholders' wealth effect and government's strategy. Thirdly, it might reflect the fact that Chinese firms acquired less attractive targets perhaps because hubris and herding behavior led to irrational investment and decreasing firm value.[30][31]

To distinguish these hypotheses, we employ both multivariate analysis and a Blinder-Oaxaca decomposition procedure to identify the source of the lower, post-Go Global underperformance. We find no evidence to support that lower abnormal return is associated with government-owned characteristics. Nor does it have any relationship with energy and natural resources and high-technology sectors, which are regarded as national strategic industries. On the contrary, the mean and estimated coefficients in the decomposition procedure suggest improved OMA performance with policy-related variables. Thus, the reason for lower abnormal returns might not come from national strategy diminishing profit value, nor hubris and herding, but from diminished prospects for extraordinary profit opportunities.

Section II in this chapter focuses on literature relevant to this study. Section III reports data and methodology. Section IV reports the empirical results. Section V draws the conclusions.

3.2. Related Literature

3.2.1. Chinese Go Global Policy

The Chinese government's promotion of overseas investment came into force with the unveiling of its "Go Out Policy" or "Going Global Strategy" -- henceforth "Go Global" – in

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[30] Firth(1997), Jensen(1986) argue that top managers employ cash only payment when they have enough cash flow and very bright prospects for post-merger performance. Mix payment, however, means acquirers tend to share risk with the targets by making the target shareholders equity-holders in the acquirer. Loughran & Vijh (1997) and Sudarsanam & Mahate (2003) find that cash payment is associated with positive and significant wealth effects. Harford et.al argue that cash-rich firms are more likely to attempt acquisition. Less controlled managers tend to spend cash in inefficient M&A activities (Harford, 1999; Harford et al., 2008).

[31] Hubris and herding hypotheses state that overconfident managers overvalue the synergy of OMAs or high reputation but low ability managers make OMA decisions simply following the leading firms in the industry, or weakly controlled managers in cash-rich firms choose to spend cash quickly in an inefficient way, please see Graham(1999) and Roll(1986) for details.

1999.[32] As a national policy, it was elevated in importance when it was adopted as part of the 10th Five Year Plan (2001-2005).[33] The nature of this promotion has taken numerous forms, and continues to evolve to the present day.[34]

One major thrust of the Go Global policy has been the loosening of controls on outward investment by Chinese firms. Outward investment requires approval by China's Ministry of Commerce, with concomitant foreign currency approval from the State Administration of Foreign Exchange (SAFE). In 2002, SAFE authorization was decentralized from the central agency to selected local authorities for projects of US$1 million or less, with an overall investment cap of US$200 million. Subsequent decentralization continued in 2005 such that foreign exchange authorization was extended to all provinces, municipalities, and autonomous regions; the local limit was increased to US$10 million; and the overall investment quota was expanded to US$5 billion. In June 2006, the overall investment quota was abolished. Meanwhile, authorization from the Ministry of Commerce was decentralized to local commercial administrations in October 2004, except for large state-owned enterprises.

A second thrust has involved direct support from the Ministry of Commerce. Some of this has consisted of informational support and bureaucratic expertise in navigating foreign investment rules. In July 2004, the Ministry of Commerce along with the Ministry of Foreign Affairs provided a "guidance list" of industries that should be preferred for outward investment. Additional support has come in the form of preferential treatment of outward-investing Chinese firms in terms of direct grants, tax benefits, low- or no-interest loans, access to foreign exchange, etc. This culminated in November of 2004 with the creation of a

[32] See "http://en.wikipedia.org/wiki/Go_Global."
[33] See "http://www.gov.cn/node_11140/2006-03/15/content_227686.htm" (in Chinese).
[34] See Hagiwara (2006) for subsequent discussion of the Go Global policy.

formal loan support system under authority of the National Development and Reform Commission and the Export-Import Bank of China.

This brief summary documents some of the changes and expansions that have occurred in China's Go Global policy since its inception in 1999. The policy is associated with at least three main motivations. First, with overwhelming foreign exchange reserves, it provides a means of reducing appreciation pressures on China's currency, the Renminbi. Second, it addresses concerns that there be sufficient resources to sustain China's growth over the middle- to long-term. And third, it presents an opportunity to modernize Chinese business via the appropriation of foreign technology and the assimilation of modern business practices. To the extent that government involvement in firms' OMA decisions is prompted by these motivations, with interventionist government control over the economy and an uncertain investor protection environment, it sets up a potential conflict between the maximization of shareholder wealth and the pursuit of national goals.

3.2.2. Policy and M&A Waves

A large literature exists to explain the phenomenon of M&A "waves" after policy, economic, social and regulatory changes.

The early M&A waves of the 1890s and 1920s in the world are purported to have been driven by antitrust legislation, while that of the 1980s appears to have been brought on by widespread market deregulation (Gregoriou & Renneboog, 2007). Sudarsanam (2003) argues that the enforcement of antitrust laws was responsible for M&A waves in the 1890s and 1920s as anti-trust policy was aimed at cracking monopolies, dominant firms were broken up and their parts divested. Subsequently, firms focused on expansion through vertical integration. Harford (1999) stresses that the M&A waves are due to deregulation of financial constraints, when companies build up large cash reserves, or when their access to external financing is eased.

Martynova & Renneboog (2005) argue that the wave of the 1980s was set off by changes in antitrust policy and the deregulation of the financial services sector. Furthermore, they claim that the medical services and pharmaceuticals sectors experienced intensive takeover activity to take advantage of cost reductions after the introduction of a new reimbursement policy in 1983 in the US.

Jovanovic & Rousseau (2002) develop the Q-theory of takeovers. They argue that takeover waves are frequently driven by industrial and technological shocks, which cause a higher degree of dispersion of corporate growth opportunities. This triggers the reallocation of resources to more productive firms and more effective management (higher Q-ratio firms).

Wells (1983a) highlights the comparative advantage of emerging giants in smaller scale markets. Lecraw (1993) and Lall (1986) argue that emerging giants invest abroad based on firm-specific advantages achieved from their home countries; such as, cheaper labor cost, nationality products, etc. Multinational enterprises (MNEs) from emerging markets are less likely to achieve efficiency and profitability compared to their developed competitors. Dunning & Lundan (2008) address government support of "resource seeking" in emerging countries, especially in energy, natural resources, and high technology industries. They argue that emerging OMAs are promoted by government policy. Emerging giants direct themselves to strategic industries in order to achieve government-sponsored policy benefits -- such as preferential loans, deregulated financial services, and favourable tax treatment -- rather than for efficiency reasons.

3.2.3. Hubris and Herding Behavior and OMA Performance

Another group of researchers highlight self-interested managerial decision-making in takeover clustering. After Jensen highlighted the agency problem in corporate governance, Roll (1986) stressed the hubris hypothesis to explain corporate takeovers on overvalued targets. He argues that managers overestimate the creation of synergy value. They usually pay too much for their targets and end up with poor performance. Scharfstein & Stein (1990) and Graham (1999) investigate herding behavior in decision-making. They find managers mimic the investment decisions of the leading firms, ignoring substantive private information, and this leads to irrational M&A decisions and lower profits.

Martynova & Renneboog (2005) argue that managerial hubris and herding behavior increase during takeover waves. Bhagat Dong, Hirshleifer, and Noah (2004) and Harford (2003) find that the highest M&A gains come at the beginning of takeover waves. Herding combined with hubris may mean that inefficient takeovers are more likely to follow efficient ones (Auster & Sirower, 2002).

3.2.4. Chinese OMAs and Government Control

With respect to China, a number of authors have noted that no discussion of Chinese OMAs is complete without special recognition of the role of the Chinese government (Huaichuan & George, 2008; Morck et al., 2008; Ping, 2007). The relationship between Chinese government and business enterprises is complicated. Government can be involved directly -- via direct ownership and control; or indirectly -- via participation in share markets. Further, different levels of government may be involved; with national, provincial, and municipal governments engaged individually, or operating together as joint ventures. This makes the distinction between government- and private-ownership blurry at best (Antkiewicz & Whalley, 2007). Liu (2005) estimates that 61.4 percent of Chinese listed companies are under local government control, 15.3 percent are under central government control, and 3.4 percent are cooperatively controlled by different levels of government. Only 12.8 percent are identified as privately controlled.[35] Similarly, Morck, Yeung, and Zhao (2008) find that 65.9 percent of shares listed on the two mainland exchanges are owned by some level of Chinese government or related government agencies.

The implications of government control are manifold. Government can influence the appointment of senior company executives, can exert direct control over the kinds of business activities undertaken and the manner in which they are implemented, and subsidize specific business activities either directly or indirectly via low- or no-interest loans from the Chinese Central Bank. A relatively large literature explores whether government control has beneficial or detrimental effects on Chinese firm performance. The evidence is mixed depending on the particular performance metric employed (Gunasekarage, Hess, & Hu, 2007; Hovey, Li, & Naughton, 2003; Qi, Wu, & Zhang, 2000; Sun et al., 2002; Wei et al., 2005; Xu & Wang, 1999). For our purposes, the salient issue is whether government control causes Chinese firms to pursue OMAs for reasons other than increasing shareholder wealth.

3.2.5. OMA Performance of Emerging Acquirers

Previous studies have come to conflicting conclusions about the response of share markets towards acquiring firms announcing OMA deals in other emerging markets. Gubbi et al. (2010) evaluate 425 cross-border acquisitions by Indian firms during 2000-2007 and report positive and significant cumulative abnormal returns of 2.58% over the eleven-day window around the announcement date. Aybar and Ficici (2009) examine 433 cross-border M&As associated with 58 large multinational firms during the period 1991-2004. They report significant, negative cumulative abnormal returns of -0.09% on the (-1,1) window.

[35] Ownership details for the remaining 7 percent were insufficient to identify the degree of government control.

Kim (2003) analyzes 270 events of overseas foreign investments (which include OMAs) by Korean firms from 1991-1997. He reports a lagged, positive market reaction on the day after announcement of 0.26%, which is significant at the 10 (but not 5) percent level. However, when he restricts analysis to the 30 largest *chaebol*-affiliates, he finds cross-border investments do not increase shareholder wealth.

3.2.6. Expected Effects of China's Go Global Policy

<u>The Demand and Supply Hypothesis.</u>

The preceding description of China's Go Global policy allows us to hypothesize about stock market responses to OMA deals by Chinese firms before and after the policy. Let the demand and supply of OMA projects for Chinese, acquiring firms be given by FIGURE 1. The acquiring firm's willingness to buy is represented by the height of its demand curve, and is the maximum amount it could pay and still earn a profit from the deal. As not all potential target firms offer the same profit opportunities, the firms' demand curve will be downward-sloping, with more profitable targets sought-after first. Likewise, target firms will be characterized by different willingnesses with respect to being acquired by the respective firms. This can arise because of an overall willingness/reluctance to being acquired, or because competition from other potential acquirers drives up a target firm's acquiring price. The result is that Chinese, acquiring firms will face an upward-sloping supply curve of OMA projects. In the absence of constraints, firms would undertake Q* OMA projects.

The vertical distance between the demand and supply curve at a given quantity represents the wealth-creation potential (rents) associated with a given OMA deal. These can be appropriated by the target firm, by receiving a price higher than its willingness to sell;

and/or by the acquiring firm, by paying a price lower than its willingness to buy.[36] Without loss of generality, let us assume that acquiring and target firms split these rents according to some fixed proportion.[37] If the acquiring firm pays a price lower (higher) than its willingness to buy for a given deal, stock markets should respond to its announcement by recording positive (negative) abnormal profits.

As discussed above, in the years preceding China's Go Global policy, firms were heavily restricted from investing overseas. Let us assume (for the moment) that government approval was given to those deals that had the greatest expected benefit to Chinese, acquiring firms. Let this quantity of deals be represented in FIGURE 1 by Q (Before Go Global) < Q*. As long as these rents were not entirely appropriated by the target firms, we would expect share markets to greet their announcements with positive, abnormal returns.

The loosening of restrictions after Go Global allowed firms to pursue more OMA deals. Ceteris paribus, these additional projects would be expected to generate smaller rents, reducing the profit gains from Chinese, acquiring firms and lowering share markets' price responses to OMA announcements. It is also possible that there could be pressure to pursue OMA deals that supported the national objectives of Go Global – such as acquiring foreign technology or locking in a long-term supply of natural resources – and that these could run counter to the private interests of shareholders. This would be represented in FIGURE 1 by firms pursuing deals beyond Q*. If this were the case, OMA deals would lower firm profits, and share markets would register negative, abnormal returns at their announcements.

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[36] Most studies of domestic M&A performance find that shareholders from target firms acquire most if not all of the benefits from M&As (Andre et al., 2004; Healy, 1992; Michael C. Jensen & Ruback, 1983; Loughran & Vijh, 1997; Masulis et al., 2007). In contrast, studies of cross-border M&As find that these deals are frequently wealth-creating for shareholders of acquiring firms (Harris & Ravenscraft, 1991; Lowinski et al., 2004; Morck & Yeung, 1992). As noted above, there are still relatively few studies of OMAs from less developed countries.
[37] All the argument requires is that (i) OMA deal approvals were positively related to the expected benefit to the Chinese acquiring firm in the pre-Go Global period, and (ii) that the demand and supply of potentials deals was similar before and after Go Global.

A key assumption in the preceding analysis is that, during the pre-Go Global period, OMA approval was positively related to the expected benefit to the Chinese acquiring firm. No doubt other factors also played a role: Political connectedness of company executives, influence of government officials associated with public ownership of the firm, and the ability of the deal to contribute to important political and national interests were likely also important. However, as long as these were not negatively correlated with the expected sizes of benefits to acquiring firms, we should still expect markets to respond with smaller abnormal returns to OMA announcements during the Go Global period compared to the years before.

The Government Capitalization Hypothesis.

The government capitalization hypothesis assumes that in the absence of Go Global, Chinese giants grow along with rapid domestic economic development. They learn by international operations experience and their behaviour is governed by rational OMA decision-making.

Possibly working against this are the actions of Chinese government. If firms purchase foreign companies by government influence rather than by narrow profit concerns, lower performance will be expected because of the conflicting interests of government and shareholders. It is well-known that governments consider factors such as social and political benefits, and are concerned with macro economic development. In contrast, shareholders care more about how to maximize their wealth in investment.

The Hubris and Herding Hypothesis.

As we argue below, the hubris and herding hypothesis is more likely to come into play with the introduction of the Go Global policy. With the reduction in financial constraints of overseas investment that occurred after Go Global, it is more likely that Chinese managers overestimated the creation of synergistic value. Similarly, firms with limited international operations experience imitated the actions of a leader or a first-mover firm in the investment-stimulated environment. As Harford, Mansi, & Maxwell (2008) discuss, weakly controlled managers choose to spend cash quickly on acquisitions and capital expenditures.[38] Thus, successful takeovers may encourage other companies to try for similar transactions. However, the other companies may not be acting from clear economic motives; hence their takeovers may not result in the same efficiency.

3.2.7. Determinants of Chinese OMA Performance

According to the above discussion, if Go Global affects the kinds of OMA deals acquiring firms undertake, government's preferences for (i) high-technology and (ii) energy and natural resources targets should be reflected in OMA performance.[39][40]

Other factors, such as method of payment (Jensen & Meckling, 1976), industry relativeness (Doukas & Lang, 2003), professional advisors (Lowinski et al., 2004), exchange rate volatility (Dewenter, 1995) with the host country have also been shown to affect OMA performance.[41][42][43] Thus, we include the mentioned determinants as control variables in our analysis.

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[38] Shareholders of emerging giants are believed to be explored in a less protective investment environment and possess less right in controlling irrational investment decision.

[39] Xu & Wang (1999) investigate ownership structure of publicly listed companies in China within the framework of corporate governance. They find profitability of Chinese firms is either negative correlated or uncorrelated with the fractions of state shares, which imply inefficiency of state ownership. Wei, Xie, & Zhang (2005) exam the relation between ownership structure and firm value across a sample of 5284 firm years of China's partially privatized former state-owned enterprises (SOE) from 1991-2001. They find that state and institutional shares are significantly negatively related to firm value.

[40] Dunning & Lundan (2008) report that governments from developing economies often use OFDI for the purpose of acquiring technology and resources. Harris & Ravenscraft (1991) find that cross-border takeovers are more frequent in R&D-intensive industries than in domestic ones. Morck & Yeung (1992) and Francoeur & Montreal (2005) find that acquiring firms experience a significantly positive stock price reaction when announcing foreign acquisitions possessing high levels of R&D.

[41] Harris & Ravenscraft (1991) argue that firms in related industries usually possess similar technologies and managerial frameworks, which are elements that lead themselves to better communication and successful post-merger integration. Hopkins (1999), Doukas & Lang (2003) find M&As in unrelated industries often leads to

3.3. Data and Methodology

3.3.1. Data

The sample analyzed in this study contains Chinese firms engaged in overseas acquisitions over 15 years from January 1, 1994 to December 31, 2009. The OMA data was drawn from Thomson's SDC Platinum M&A Database. The selection criteria are as follow:

-- Merger and acquisition transactions announced between January 1, 1994 and December 31, 2009

-- Merger and acquisition transactions must be completed

-- Chinese bidders and non-Chinese targets[44]

-- The bidders are listed in Shanghai, Shenzhen, Hong Kong or U.S. stock markets

-- Non-Financial firms[45]

The time series stock prices and market indices data come from DataStream. Returns were computed by the logarithm form of adjusted stock prices, $\ln(P_t / P_{t-1})$, as discussed in Strong (1992). Shanghai Composite Index, Heng-Sang Index and S&P 500 Composite are

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faulty strategic decision-making and misunderstandings in communication between the acquirers and targets. These are obstacles to post-merger synergy.

[42]Servaes & Zenner (1996) point out professional advisors help with a more informed M&A decisions and better post-merger integration. However, Lowinski,F., Schiereck,D & Thomas,T. W.(2004) figure out bidders should tolerate expenditures of huge sums of money as fees for their direction. Nevertheless, there are cases of failure M&As under the supervision of professional advisors.

[43] Cushman (1985), Froot & Stein (1991), Cebenoyan, Papaioannou, & Travlos (1992) and Dewenter (1995) provide evidence that exchange rate variable clearly impacted on corporate performance. However, Pettway et al. (1993) find magnitude of firms' gains depend more on the relative market power among the buyers and sellers and on the nature of the assets being purchased, rather than on variation in exchange rates.

[44] There are only 112 Chinese outbound M&A events in SDC M&A database in 1994-2008 period when I searched by "public bidders" criteria. However, when we go further to employ "government" and "Hong Kong bidder" criteria, I got another 120 Chinese listed companies. I have kept records for the "Hong Kong bidder" ones that included in our sample as we visited their company websites and there are strong evidence showing they are Chinese mainland firms listed in Hong Kong (According to their ownership/location of headquarter, business/ nationality proportion of employees).

[45] Financial firms are subject to special accounting and regulatory requirements, making them difficult to compare with other firms.

selected as the local market indices respectively. The estimation period contains 126 daily returns before the event window (21 days).

3.3.1.1. Time Distribution of Chinese OMAs -- Before and After "Go Global"

The initial sample contains a total 198 events. However 41 events were eliminated with more than 50% zero daily returns over a 147-dayinvestigation period.[46] Table 3.1 shows the distribution over time of 157 Chinese outbound M&A transactions in the final sample.[47]

There is a strong event and deal value cluster in the period 2002-2009. The number of transactions peaked in 2009, accounting for 29 deals. The highest average transaction value is in 2005 and 2006; 707.27 and 943.36 million USD respectively. Apparently, Chinese enterprises became more active in OMA activities after Go Global. Both deal number and deal value soared after 2002. Average transaction value rose from USD 68.95 million per year in 1994-2001 to USD 485.99 million in 2002-2009. To our great surprise, Chinese OMA deals grew dramatically even in the world recession. Data shows 45% of the Chinese OMA deals happened during the year 2007-2009, though there was a sharp drop in average transaction value to USD 172.65 million per year.

3.3.1.2. Target Location of Chinese OMAs

Table 3.2 reports the distribution of Chinese OMAs by target location. The sample shows developed targets account for approximately 69% of completed Chinese overseas deals, and 65% of the available deal value in the year 1994-2009. Asian targets rank second both in number of deals and deal value. 19% of deals and 22% of available deal value come from

[46] 147 days comes from 126 days in the estimation period plus 21 days in the event window.

[47] Even accounting for the fact that our study includes (i) more years and (ii) listings in U.S. markets, we still identify many more OMA events than Chen and Young (2009). One possible explanation for this discrepancy is that Chen and Young (2009, page 8) hand-collected their data through news announcements published by the China Mergers and Acquisitions Association (CMAA). In contrast, we identified our OMAs through the Thomson Reuters SDC Platinum database.

Asia. Africa ranks first by its average USD 1447.25 million per deal. We note that a disproportionate number of OMA activities target Chinese Hong Kong firms, followed by the United States and Australia.[48]

3.3.1.3. Industry Distribution of Chinese OMAs

Table 3.3 reveals the industry distribution of Chinese OMAs. It is obvious Chinese OMAs cluster in high technology and energy, and the natural resources sector. The Telecommunication and Electronics, Prepacked Software sector achieves the highest frequency in transactions; whilst the Energy and Natural Resources sector attracts 67% of the outflow capital. When we break the time period into before and after Go Global, we notice that most M&As in energy and service sectors happened after the policy. OMA deals tripled in the Telecommunication and Electronics, Prepacked Software and Manufacturing sectors in 2002-2009.

3.3.1.4. Market Distribution of Investigated Stocks

Some Chinese firms only list in foreign markets. Others list in multiple markets. Therefore, stock returns from cross-listed markets (Hong Kong, U.S.) are included in the sample. There are 213 observations in total when multi-listed observations are included.[49] When aggregated performance of 157 events is estimated, we select among cross-listed shares by choosing the one with greatest liquid.[50] The aggregated sample consists of 64 mainland listings, 62 HK listings and 31 US listings.

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[48] Hagiwara (2006) suggests that a substantial portion of Hong Kong OMA activity is in fact "roundtrip" investment that detours outside the mainland to take advantage of various tax, trade, and regulatory incentives. However, HK targets dropped sharply from 74.19% of the target location before policy to 18.57% in crisis period after policy.

[49] 64 mainland listings, 76 HK listings and 73 US listings.

[50] Trading volume and market depth are considered as representatives of market liquidity. Therefore, I select highest trading volume ones when equities possess considerable higher market capitalization. If market capitalization is two or more times larger than highest trading volume ones among multi-listings, I come back to equities with highest market capitalization.

3.3.2. Event-time Approach

We employ the event-time approach to evaluate wealth effects of Chinese overseas M&A. Daily stock returns are collected over a 126-day estimation period. For the 21- day event window, abnormal returns (AR) of individual stocks are calculated as the difference between the actual individual return, (R_{it}), and the expected return, $E(R_{it})$, from the estimation period:

(1) $AR_{it} = R_{it} - E(R_{it})$.

where R_{it} and R_{mt} are the daily returns of share *i* and the market portfolio at time *t* during the estimation period.

The market model is specified as

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

This model is estimated to produce estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$. These are then used to calculate expected returns during the test window as follows:

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

Thus

(4) $AR_{it} = R_{it} - \left[\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right]$

Average abnormal return (AAR) and average cumulative abnormal return (ACAR) are used to estimate Chinese overseas M&A performance. To examine the significance of mean standardized residual between any two dates, we employ the test procedure proposed by Patell (1976) and Doukas & Travlos (1988) to investigate the significance of 21-event day abnormal returns.[51]

AAR and ACAR are calculated as follow. For a sample of N firms:

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[51] Please see appendix for details.

$$(5)\quad AAR_t = \frac{1}{N}\sum_{j=1}^{N} AR_{jt}$$

$$(6)\quad ACAR_{T1,T2} = \frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1}^{T_2} AR_{jt}$$

The expected value of AR_t is zero in the absence of abnormal performance. To examine whether the average daily abnormal return is statistically different from zero, the average standardized abnormal return ($ASAR_t$) is calculated as

$$(7)\quad ASAR_t = \frac{1}{N}\sum_{j=1}^{N}\frac{AR_{jt}}{S_{jt}}$$

where S_{jt} is the square root of firm *j*'s estimated forecast variance at time *t* during the test window,

$$(8)\quad S_{jt} = [S_j^2[1 + \frac{1}{L} + \frac{(R_{mt} - \overline{R_m})^2}{\sum_{k=1}^{L}(R_{mk} - \overline{R_m})^2}]]^{1/2}$$

and S_j^2 is the residual variance for security j from the market model regression, L is the number of observations during the estimation period, R_{mk} is the return on the market portfolio for the kth day of the estimation period, R_{mt} is the return on the market portfolio for day *t* of the test period, and $\overline{R_m}$ is the average return of the market portfolio for the estimation period.[52] It follows that:

$$(9)\quad Z_{Daily} = \sqrt{N}\,ASAR_t$$

Similarly

$$(10)\quad ASCAR_{T1,T2} = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=T1j}^{T2j}(\frac{AR_{jt}}{S_{jt}})$$

$$(11)\quad Z_{Interval} = \sqrt{N}(ASCAR_{T1,T2}) / \sqrt{T_{2j} - T_{1j} + 1}$$

[52] The equations 6-10 are from Doukas & Travlos (1988).

3.3.3. Performance Determinants of Chinese OMAs

Part one of our analysis estimates abnormal returns both for the whole period, and separately for the pre- and post Go Global periods. Part two of our analysis attempts to explain observed differences between the two periods. We examine eight characteristics of deals. These are described in Table 3.9. *GOVTOWN* is a dummy variable that identifies whether the acquiring firm is a government-owned enterprise.[53] *NATREL* and *ITIN* are variables that indicate whether the target firm is located in the natural resources/energy or high technology industries. *THK* is a dummy variable that indicates whether the target firm is located in Hong Kong. The variable *INDREL* indicates whether the target firm is located in the same industry as the acquiring firm (as measured by 2-digit SIC code). *ADVISOR* is a dummy variable that identifies whether the acquirer employs professional advisors. *FEX* shows the percentage of depreciation/appreciation of Chinese RMB against USD on a daily basis. *CASH* is a dummy variable indicating whether the transaction is cash only payment.

The first three variables are designed to capture the influence of Go Global on firms' OMA decisions. Firms that are government-owned should be more willing to trade off the interests of other shareholders in favour of national strategic interests. Further, since two of the three motivations underlying Go Global are to secure natural resources and appropriate new technologies, we would expect to see the lower abnormal returns in the Go Global period related to deals with target firms in these industries. The remaining five variables are control variables in M&A transaction details.

Differences in the respective contributions of those determinants may explain differences in announcement returns. Accordingly, we will estimate the following three models. Model 1 regresses the firm's three-day cumulative abnormal return around the

[53] The concept "government-owned enterprise" in my study means a firm that ultimate parent is defined as Chinese government in SDC Platinum.

announcement day, CAR (-1,1), against a policy dummy variable. Model 2 adds three policy-related variables (GOVTOWN, NATREL and ITIN) to Model 1 to see whether they have any influence on the policy dummy because of omitted variable bias.

For the same reason, we add 5 more control variables to Model 3: THK, INDREL, ADVISOR, FEX and CASH. Chinese RMB appreciated against the USD in 1994-2009. Currency appreciation is highlighted as one of the important determinants of OMA performance. Therefore, we include it as a control variable in Model 3. About 37% of Chinese OMA targets are in HK, so we'd like to control this when testing performance determinants. The other 3 variables are included to investigate misbehaviour of top managers. Generally speaking, if related industry dummy gets a negative coefficient against performance, it indicates OMAs haven't generated synergy and implies an inappropriate investment decision-making. Similarly, professional advisors are believed to contribute value to OMA transaction. If we estimate a negative relationship between OMA performance and professional advisor, it implies top managers have made a wrong decision when choosing advisors, or have paid too much for their services. Either of these possibilities is consistent with the hubris or herding hypothesis. As mentioned in the literature review above, cash-only payment is a signal of positive abnormal returns. A negative relationship with performance also suggests that top managers abuse their power on excessive cash flow, consistent with the hubris and herding hypothesis.

Define the variable Policy to take the value 1 during the Go Global period. The three models are given below.

<u>Model 1</u>

(12) $CAR(-1,1) = \beta_0 + \beta_1 POLICY + error_i$

<u>Model 2</u>

(13) $$\begin{aligned}&CAR(-1,1) = \beta_0 + \beta_1 POLICY + \beta_2 GOVTOWN\\ &+\beta_3 NATREL + \beta_4 ITIN + error_i\end{aligned}$$

<u>Model 3</u>

(14) $$\begin{aligned}&CAR(\text{-}1,1)_i = \beta_0 + \beta_1 POLICY + \beta_2 GOVTOWN_i + \beta_3 NATREL_i + \beta_4 ITIN_i\\ &+\beta_5 THK_i + \beta_6 INDREL_i + \beta_7 ADVISOR + \beta_8 FEX + \beta_9 CASH + error_i\end{aligned}$$

We will estimate the coefficient on the POLICY variable and observe what happens to the coefficient as additional "policy" variable are added to the model.

3.3.4. Blinder-Oaxaca Decomposition Procedure

An alternative approach to explain the difference in estimating CAR(-1,1) before and after Go Global is the Blinder-Oaxaca Decomposition method (Blinder, 1973; Oaxaco, 1973). This procedure is commonly employed in the labor economics literature to analyze wage differences between two different groups (e.g., male and female workers). It decomposes the mean difference in the dependent variable, e.g. wages into the portion that can be explained by (i) differences in the characteristics of the two groups, and (ii) differences in the estimated coefficients in an Equation (14)-type regression, without the policy variable.

Let $\bar{Y}_1$ and $\bar{Y}_2$ represent the sample means of the dependent variable for two groups. It follows that $\bar{Y}_1 = \bar{\boldsymbol{X}}_1 \hat{\boldsymbol{\beta}}_1$ and $\bar{Y}_2 = \bar{\boldsymbol{X}}_2 \hat{\boldsymbol{\beta}}_2$; where $\hat{\boldsymbol{\beta}}_1$ and $\hat{\boldsymbol{\beta}}_2$ are the estimated coefficients from regressing Y on $\boldsymbol{X}$ for the two groups, and $\bar{\boldsymbol{X}}_1$ and $\bar{\boldsymbol{X}}_2$ are the vector of sample means of the respective explanatory variables. Two common methods for decomposing $\bar{Y}_2 - \bar{Y}_1$ are

(15a) $\bar{Y}_2 - \bar{Y}_1 = \hat{\boldsymbol{\beta}}_1\left(\bar{\boldsymbol{X}}_2 - \bar{\boldsymbol{X}}_1\right) + \bar{\boldsymbol{X}}_2\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$, and

(15b) $\bar{Y}_2 - \bar{Y}_1 = \hat{\boldsymbol{\beta}}_2\left(\bar{\boldsymbol{X}}_2 - \bar{\boldsymbol{X}}_1\right) + \bar{\boldsymbol{X}}_1\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$.

Method A weights the difference in characteristic sample means $\left(\bar{\boldsymbol{X}}_2 - \bar{\boldsymbol{X}}_1\right)$ by $\hat{\boldsymbol{\beta}}_1$, and the difference in estimated coefficients, $\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$ by $\bar{\boldsymbol{X}}_2$. Method B uses the weights $\hat{\boldsymbol{\beta}}_2$ and $\bar{\boldsymbol{X}}_1$, respectively.

If "Go Global" directed investment towards targets that benefitted national strategic interests at the expense of firm value, this should be reflected in either the effect of the differences in sample means, $\left(\bar{\boldsymbol{X}}_2 - \bar{\boldsymbol{X}}_1\right)$, or the differences in estimated coefficients, $\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$, or both. For example, suppose natural resource firms generally make less attractive targets for Chinese acquirers than firms in other industries. Then an increase in the number of *NATREL* deals would be associated, ceteris paribus, with lower abnormal announcement returns. In other words, the effect of Go Global would be reflected in the $\left(\bar{\boldsymbol{X}}_2 - \bar{\boldsymbol{X}}_1\right)$ component.

Alternatively, suppose that prior to Go Global, Chinese firms only acquired natural resources targets that were likely to increase shareholder wealth. But after Go Global, government policy-makers encouraged them to acquire natural resources targets even if it was likely to lower profits. In this case, the effect of Go Global would show up in a lower estimated coefficient on the *NATREL* variable; and the effect of Go Global would be reflected in the $\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$ component.

We also use multivariate regression analysis to get at the same question. Specifically, we investigate the extent to which explanatory variables associated with the (i) Government Capitalization and (ii) Hubris and Herding hypotheses can explain differences in abnormal returns before and after Go Global. An advantage at this approach is that we can use a pooled sample and get larger sample sizes than with the decomposition approach. In contrast, the Blinder-Oaxaca decomposition approach relies on breaking down the sample into before and after policy periods and comparing both their respective means and estimated coefficients. It allows us to calculate the percentage contribution of specific variables to the observed difference in abnormal returns between the Pre- and Post- Go Global periods.

3.4. Results of Empirical Analysis

3.4.1. General Performance of Chinese OMAs

Table 3.4 shows daily performance of Chinese OMAs in the test period. We employ event study methodology to estimate announcement effects of OMAs on stock returns. Day 0 is defined as the announcement date. The market model is applied to estimate benchmark returns. We report both average abnormal returns (AAR) and average standardized abnormal returns (ASAR). We estimate a positive 0.44% average abnormal return (AAR) on day 0, though this is insignificantly different from zero. Further, returns are positive for each day over the (-1,1) period, though the returns for each day are insignificant. Standardized abnormal returns behave similarly. However, abnormal returns become negative after day 1, though daily returns continue to be insignificant. We hypothesize that markets may retreat from their optimistic evaluation once they get better informed about it. Since we could not make a conclusive judgment only by daily performance, we move to test interval abnormal returns.

Table 3.5 reports interval responses for Chinese OMAs. We choose intervals before, within and after announcement. For example, (-10,-1) is the ten day interval before the announcement. The interval CAR (-1, 1), indicates a 1.2% positive abnormal return on the three day interval around the announcement day. This is significant at the 5% level. However, over the longer (-10, 10) interval, ACAR is very close to zero, (0.06%), and insignificant. These results suggest that markets responded positively to announcements of Chinese OMAs over the 1994-2009 period, and the market is efficient in general because the announcement effect is only significant on day (-1,1) window.

3.4.2. Performance in Three Listing Markets

In this next section we take a closer look by analyzing returns from each of the three markets (see Table 3.6). If we examine daily returns over the (-1,1) period, we find that across the 3 markets, each of the ACAR values are positive with one exception: Day 1 in the mainland market. Two are significant, and they are each positive: Day (-1) in the mainland, and Day (1) in the US. Outside the (-1,1) window there are some puzzling results (such as Day -7 in the US). Given the large number of daily results, some of these significances may be spurious.

Since the daily ARs are noisy, we look to the interval performance of Chinese OMAs in Table 3.7. Chinese mainland markets show significant positive abnormal returns of 2.20% and 1.49% before the announcement over intervals (-10,-1) and (-5,-1) respectively, at 5-percent level. Thus, Chinese mainland markets responded positively before the announcement, which is evidence of information leakage. In the Hong Kong market, we find a 1.17% positive and significant abnormal return over the interval (-1, 1), at the 5-percent level. In the U.S., none of the intervals showed significant abnormal returns. This suggests that markets behave differently to the initial announcements of Chinese OMAs due to diversified information sets.

3.4.3. Performance Comparison Before and After "Go Global"

Table 3.8 compares market responses to Chinese OMAs before and after Go Global. We find positive ACARs (-1,1) in both periods, 3.39% before "Go Global" and 0.66% after. These are significant at the 10% and 5% levels, respectively. ACAR(-1,1) before "Go Global" policy is 2.73% higher than ACAR(-1,1) after. This suggests that "Go Global" may have had negative effects on firms' performance. However, since the difference is not significant, these results are not conclusive.

3.4.4. Sample Description on Performance Determinants

Table 3.9 describes all the variables employed in the subsequent analysis of the differences in AARs before and after Go Global. Table 3.10 reports summary statistics. The dependent variable, CAR (-1, 1) has a mean value of 1.2% with a maximum of 63.2% and minimum of -13.8%. For the policy-related variables, 80% of the OMA events happened after Go Global (POLICY). Having so many deals occur in the Go Global years suggests that the Go Global policy sparked much OMA activity. 47% of the acquirers are government-owned enterprises (GOVTOWN). Targets in natural resources (NATRES) and high-technology sectors (ITIN) constitute about 26% and 34% at all deals respectively. With respect to the control variables, we note that 37% of all deals are targeted in HK. Half of the deals are between related industries (INDREL). 30% of acquirers take advantage of professional advisors in their transactions (ADVISOR). On average, Chinese RMB appreciated against the USD in the 1994-2009 period (FEX). 56% of the transactions are cash payment only. We also list alternative variables for robustness checks. Cultural Distance is an index describing cultural differences between China and the host countries (CULDIS). A larger number indicates a bigger cultural difference. Table 3.10 reports that the average cultural distance between China and the host countries is about 1.44. 76% of targets are in developed nations or areas (DEVDC).[54] The average transaction value is USD 292 million (TRAVALUE), the average market capital of acquirers is USD 11,433 million (MV6b) with a mean book-to-market ratio (BM) is 0.6. 38% of the acquirers list in the Hong Kong stock exchange (HKM), whilst 20% of them list in the US (USM). 44.6% of OMA deals happened after the 2007 financial crisis (CRISIS).

[54] 54% (58/108) are in HK, and the reminder of the 46% (50/108) are in other developed nations or areas.

As noted above, the fact that approximately 58% of the acquirers are cross-listed firms in foreign stock markets (namely HK and US), implies that firms with international experience are more likely to invest abroad. Unfortunately, data for cultural distance, transaction value and book-to-market ratio are not available for all observations.

Before we use the variables in our regression equations, it is useful to observe the simple correlation between variable pairs. In Table 3.11, we find 4 correlation coefficients larger than 0.5. These are CULDIS and THK, INTRAVALUE and ADVISOR, CRISIS and FEX, and LNMV6B and LNTRAVALUE.

A correlation coefficient of 0.91 between CRISIS and FEX suggests that RMB appreciation moves generally in the same direction as the financial crisis. This suggests that substantial multicollinearity could occur if both variables were included in a model. Not surprisingly cultural distance is highly negatively correlated with HK targets (-0.77) because HK and the Chinese mainland are "culturally close". Transaction value achieves a 0.56 correlation coefficient with advisor, and firm sizes get a 0.57 correlation coefficient with transaction value. This implies that firms are more cautious and tend to invite professional advisors for help when the transaction value is larger. Bigger Chinese acquirers are more likely to initiate larger transaction deals.

3.4.5. Policy Impact Analysis by Multivariate Regressions

Table 3.12 reports OLS regression results of "Go Global" policy models using our total sample of 157 Chinese OMA events. It is noteworthy that the policy dummy (POLICY) has a negative coefficient in each of the three regressions. Cumulative abnormal returns on the (-1,1) interval are approximately 3 percent lower in the Go Global period, and is relatively unaffected by the inclusion of other explanatory variables. However, the POLICY coefficient is insignificant in all three models.

However, we find that the high-technology dummy (ITIN) is negatively and significantly (at the 10-percent level) associated with Chinese OMA performance. Interestingly this indicates that high-technology OMAs generally underperform other industries. Model 2 reports a 2.8% lower CAR (-1,1) on Chinese OMAs in high-technology sector. Model 3 reports an estimate that is 2.5% lower. Although high-technology targets tripled in deal number after policy, its proportion of all Chinese OMAs reduced from 35.5% to 27% in the sample after policy. This likely reflects an industry performance gap rather than a policy impact.

Finally we note that the R^2s are very low for all three models. We cannot reject the null hypothesis that all coefficients in each model equal zero. In other words, none of the explanatory variables are significantly related to the initial responses of markets to OMA announcements.

3.4.6. Policy Impact by Blinder-Oaxaca Decomposition Analysis

3.4.6.1. Comparison of Sample Means and Estimate Coefficients

We next employ Blinder-Oaxaca decomposition to compare sample means and estimated coefficients of policy-related and other control variables before and after “Go Global”. Further, we investigate their contribution to OMA performance in the pre- and post policy period. Sample means and the results of regression analysis for the before and after Go Global periods are reported in Table 3.13 (See panels A and B).

As noted above, 80% of OMA deals were completed after Go Global.[55] The sample mean section shows that the percent of government-owned acquirers dropped from 55% to 45%.[56] On the other hand, the huge domestic demand for energy and natural resources is reflected by

[55] Furthermore, 45% of the deals are executed after world financial crisis. It seems that Chinese economy is less hammered by the world financial crisis due to intensive financial control. On the contrary, Chinese acquirers are motivated to pursue foreign targets at lower expenses during the world recession period.
[56] And even 31% in crisis period.

the sharp climb in energy and natural resources OMAs, from 3% to 33%. After Go Global, more OMAs targeted firms in related industries and used professional advisors. Fewer HK targets were involved.

Panel A of Table 3.13 reports the results of OLS estimation of Equation (13) without the policy variable. To some extent, it reveals Chinese acquirers are making progress in handling OMA with preferred policy and more international operation experience. For policy-related variables, natural resources OMAs change their estimated sign from negative to positive, which is suggestive of improving performance after policy. Coefficients on government-owned and high technology dummies are less negative after policy, but not significant.

Panel B of Table 3.13 uses OLS to estimate Equation (14) without the policy variable. We add 5 control variables to the policy-related variables. The results reveal that 4 out of 7 variables change their estimation coefficients from negative to positive, though many of them are not significant. It seems that most of the estimated coefficients of control variables (associated with the hubris and herding hypothesis) become “rational” after policy. Industry-relatedness ceases having a negative impact; likewise for professional advisors and cash-only transactions.

3.4.6.2. Blinder-Oaxaca Analysis

Table 3.14 reports the results of applying the Blinder-Oaxaca decomposition to the difference in *ACAR* values in the pre- and post-Go Global periods. Changes in (i) mean sample characteristics, $\left(\overline{\boldsymbol{X}}_2 - \overline{\boldsymbol{X}}_1\right)$, and (ii) estimated coefficients, $\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$, are identified by “Means” and “Coefficients” respectively. The numbers in the table represent the percentage difference “explained” by the respective change for each variable, including changes in the estimated value of the constant.[57] A positive number suggests that the change contributed to the difference in *ACAR* values. A negative number suggests the opposite; namely, that the observed gap is smaller as a result of the respective change. We are looking for variables with large positive values for either "Means," "Coefficients," or both to identify the contributors to negative ACAR gap. A value of 100 indicates that the respective change counts for 100 percent of the difference in ACAR (-1,1) before and after Go Global.

For example, average cumulative abnormal returns on the *(-1,1)* window were approximately 2.73 percent lower during the Go Global years (cf. $ACAR_{2002\text{-}2009}$ - $ACAR_{1994\text{-}2001}$ = -0.0273 in Table 14). At the same time, a higher percent of deals involved targets in the *NATRES* industries. Thirty-three percent of OMA deals targeted *NATRES* firms after Go Global, compared to only three percent before (cf. TABLE 3.13).

Panel A of Table 3.14 reports that approximately -30 percent (= 101.0-130.9 using Method A; = -17-13 using Method B) of the 2.73 percent decrease in abnormal returns during Go Global can be "explained" by the combined effects of the changes in means and estimated coefficients associated with the NATRES variable. This suggests that the lower abnormal return is smaller in absolute value as a result of the change in the policy-related variable *NATRES.*

The other two policy-related variables, *GOVTOWN* and *ITIN*, also explain a "negative" share of the change in ACAR (-1,1): -198.3 and -150 percent respectively. This again indicates the decrease in abnormal return is not as low as it might otherwise be because of the change of the two policy-related variables. In summary, the results of this analysis suggests that the policy-related variables are not contributing to the negative ACAR gap.

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[57] Note that the "Sum" of the "Mean" and "Coefficients" contributions over all variables (including the constant term) must equal 100 percent.

The addition of more control variables in Panel B (*THK*, *INDREL*, *ADVISOR*, *FEX*, *CASH*) does not change the outcome very much. All the 3 policy-variables are found to make negative contributions to the ACAR gap: *NATRES* (-48.1%), *GOVTOWN* (-105.8%) and *ITIN* (-191%). This is consistent with the preceding results in Panel A.

Further, the control variables *THK (-212.5%)*, *INDREL (-81.7%)*, *ADVISOR (-29.3%)*, *FEX (-300.4%)* and *CASH (-69.5%)* also fail to explain the decrease in cumulative abnormal returns during Go Global. On the contrary, the decomposition results suggest that the observed ACAR gap before and after policy would be larger without the changing of the above variables.

In conclusion, the Blinder-Oaxaca decomposition, like the multivariate analysis before it, finds no support for the hypothesis that the lower abnormal returns during the Go Global period are due to changes associated with one or more of the listed variables. Indeed, the sum of the associated contributions suggests that the difference in *ACAR* values would have been even larger were it not for changes in these variables.

Table 3.14 is noteworthy for two additional thing: one for what it doesn't show, and one for what it does. First, there is no firm characteristic that is consistently identified with the decline in positive announcement effects during the Go Global period. Second, the decline is "explained" by the constant term. This is consistent with the fact that it is the overall increase in the number of deals -- neither government-influenced investment pursuing public interests at the expense of private shareholders, nor hubris and herding behaviour of top managers -- that is responsible for lower announcement returns during the Go Global period.

3.5. Conclusion

In this study we construct a comprehensive data set composed of all Chinese, overseas mergers and acquisitions (OMAs) activities over the period 1994-2009. We then analyze stock market returns centered on the announcement dates of these OMAs. While there has been much discussion in the popular press regarding Chinese OMAs, to date there has been little empirical analysis of this subject. Previous studies have either failed to undertake a thorough analysis of the underlying data, or have not been comprehensive in their coverage of Chinese OMA activities. This chapter does both.

Our analysis is motivated by two questions:

1. Do Chinese OMAs create value for shareholders?
2. Does the Go Global policy damage shareholders' wealth?

We answer these questions using an event-study methodology to investigate announcement effects of overseas mergers and acquisitions (OMAs) by Chinese, acquiring firms over the 1994-2009 period.

The first question is of interest because of the heavy involvement of the public sector in the ownership of Chinese firms. This raises concerns that OMA decisions by Chinese firms may not be concentrated on maximizing shareholder wealth. Our analysis finds no support for these concerns. We find some evidence that markets positively evaluated announcements of OMAs by Chinese acquiring firms, and no evidence that these announcements were negatively evaluated.

With respect to the second question, our theoretical analysis identifies three possible effects of the Go Global policy. First, as Go Global relaxed restrictions on OMAs, it allowed Chinese, acquiring firms to pursue additional, albeit less profitable deals. Second, it may also have re-directed investment towards industries having critical strategic value, such as resource and technology industries. Last but not the least, hubris and herding behaviour of top managers may have contributed to increased OMA deals by Chinese, acquiring firms. While the first effect should be wealth-increasing for shareholders, these additional deals could lower the average benefit of a deal to Chinese acquirers if only the most profitable deals were approved during the pre-Go Global period. The second and third effects could be wealth-decreasing if Chinese firms were led to sacrifice shareholder interests in behalf of progressing national strategic goals or due to agency problem in corporate governance. Thus, while all effects would be reflected in lower abnormal returns during the Go Global period, only the last two effects would be wealth-decreasing.

Our empirical analysis confirms that there were more deals during the Go Global period, and that the average benefit of these deals, as measured by market responses to announcements of OMA deals, was lower during the Go Global period, though the decrease was not statistically significant. However, we find no evidence of negative abnormal returns under Go Global.

To further investigate the second effect, we use multivariate analysis and a Blinder-Oaxaca decomposition procedure (Blinder, 1973; Oaxaca, 1973) to determine whether the lower abnormal returns associated with the Go Global period are due to variables associated with government strategy. We find no evidence that the lower returns were associated with firms being government-owned, or with deals being natural resources or high-tech-related. Nor do we find any evidence that managers were less concerned with increasing shareholder wealth in the Go Global years.

In conclusion, under Go Global there have been more deals with generally lower expected benefits to shareholders. However, there is no evidence that Go Global has caused Chinese acquiring firms to sacrifice shareholder's wealth in order to pursue national interests. Nor does top managers' hubris and herding behaviour mislead OMA decision making. The decrease in OMA performance in recent years may simply reflect diminishing returns to Chinese OMAs.

Chapter Four An Analysis of the Long-run Performance of Chinese Overseas M&As: 1994-2008

This chapter examines the long-run performance of Chinese OMAs. We study 122 deals over the 1994-2008 period.[58] We focus on the one-year, two-year, and three-year returns after an OMA event occurs. While we find some evidence of significant abnormal returns over the one and two year horizon, by the third year after an OMA event, these returns become small and insignificant. The one consistent finding that we obtain is that government ownership is negatively and significantly related to long-run performance of Chinese OMAs.

[58] Since this chapter is concerned with long-run performance, and sufficient 3-year time series data is unavailable for deals effective after December 31, 2008, there are fewer observations.

4.1. Introduction

China's remarkable growth was again evidence in 2010 with a 10% GDP growth rate, the highest in the world.[59] However, it is clear that the Chinese economy is at a transition point. Traditional labour intensive, trade-oriented industries are facing increasing challenges in the world recession. The development of high-energy consuming, high-pollution firms in China are damaging the environment, and intensifying resource shortages. To make matters worse, labour disputes in Guangdong suggest that the cheap "unlimited" supply of blue-collar workers is now falling short of demand. The result must be an increase in wages, which some are concerned will stifle growth in China.[60]

Beginning in the 1980s, China embarked on a strategy of enhancing industry concentration ratios (CR) and competitive power in the global market, and restructuring industry.[61] This same strategy continues today. Beijing announced the scrapping of export tax rebates for hundreds of products on June 23rd, 2010. Included in the list were many high-energy consuming and high-pollution industries.[62] As a result of substantial appreciation of the Chinese Renminbi, overseas merger and acquisitions provide an alternative channel to increase industry CRs and restructure industry.[63]

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[59] Details please see AB Practice, June, 2010, pg 11.

[60] On June 6th, the owner of Foxconn double the basic pay it previously offered, following a string of widely publicised suicides; on the same time, Honda Guangdong Branch suffered a strike requesting pay rise. Details please see The economist June 12th, 2010, pg88.

[61] The Concentration Ratio is the percentage of market share held by the largest firms (m) in an industry. $CR_m = \Sigma^n_{i=I} x_i$; Therefore it can be expressed as: $CR_m = s_1 + s_2 + ... + s_m$ where s_i is the market share and m defines the i^{th} firm. No concentration: 0% means perfect competition or at the very least monopolistic competition. If for example CR_4=0 %, the 4 largest firm in the industry would not have any significant market share. Total concentration, 100% means an extremely concentrated oligopoly. If for example CR_1= 100%, we talk of a monopoly. Details please see http://en.wikipedia.org/wiki/Concentration_ratio.

[62] For example, steel and petrochemical, agriculture products are on the list. Details please see http://business.sohu.com/s2010/quxiaotuishui/

[63] Under continuous pressure to end the renminbi's peg to the dollar from the west, China announced to allow more flexibility of its currency exchange rate on June 19th,2010. Benn Stell, Lesson from the 1930s for a rising renminbi, Financial Times, June 23, 2010. pg 9.

Overseas mergers and acquisitions (OMAs) are an ideal strategy for the Chinese government to help firms increase their size and compete successfully with rivals in the marketplace. Chinese firms can purchase technology, market networks, human capital, and/or intangible assets that would have taken years or decades to build up by themselves. They also enable the acquisition of valuable energy and natural resources.

In 1999, Beijing initiated its "Go Global" policy. In 2001, China became a member of the WTO. Since then, China has embarked on a remarkable path of resource-seeking overseas M&A growth. Chinese overseas M&A transactions have continued to expand through the world financial crisis.[64] Since half of the acquirers are government-owned enterprises and many of the rest have stake government ownership are heavily influenced by government, we can infer that the Chinese OMA wave is part of government's strategy of long term development. Furthermore, since Chinese OMAs have been clustered in the energy, natural resources and high technology industries, we are interested in testing how these M&As have fared in the long run.

In summary, this chapter investigates Chinese OMA performance and their interaction with industry restructuring in the period of 1994-2008.[65] Since China is a typical government-oriented economy, short-term profitability may not be the most important concern. Of greater importance may be whether these OMAs help the government to achieve its industry restructuring goals and whether these economic investments are profitable in the long term.

Our research questions are:

1. Do Chinese OMAs create value for shareholders in the long run?
2. What are the determinants of Chinese OMA performance in the long run?

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[64] Please see table 1-3 for details.

[65] Due to three years time series stock prices after OMA are needed to evaluate long-term performance in calendar-time approach, Chinese OMAs in 2009 are not included.

We investigate 122 Chinese OMA events in the 1994-2008 period. We employ the Calendar-time approach to test long term OMA performance over a 3-year horizon. We find no evidence of significant returns over the 3-year horizon. However, we do find some evidence that long-term OMA performance is correlated with industry characteristics. Interestingly, OMA long-term performance appears to be greater after Go Global compared to before. There is some evidence to suggest that the opposite result holds in the short-run.

Finally, government negatively and significantly correlated with long term OMA performance. Government-owned acquirers underperform private acquirers by 10-22%.

Due to time period data limits, there are few studies on long-term OMA performance for emerging acquirers. Our study fills that gap. To the best of our knowledge, this is the first study to investigate the long-run performance of Chinese OMAs. Among other things, our results suggest that government efforts to pursue national strategic goals do not harm the long-run wealth of shareholders.

The chapter proceeds as follows. Section 2 discusses related literature. Section 3 presents data and methodology. Section 4 reports the results and Section 5 concludes.

4.2. Related Literature

4.2.1. Industry Restructuring and The Chinese OMA Wave

Much research has documented merger clusters by industry. Mitchell & Mulherin (1996) study industry-level patterns in takeover and restructuring activity during the 1982-1989 period. They find significant differences across industries. Andrade, Mitchell, & Stafford (2001) hypothesize that merger activity is the result of industry-level shocks. These shocks include: technological innovations, which can create excess capacity and the need for industry consolidation; supply shocks, such as oil prices; and deregulation. For these and other reasons, most papers control for industry when examining M&A performance (Lyon et al., 1999; Savor & Lu, 2009; Wei et al., 2005). The restructuring of industries has implications for firms' short- and long run OMA performance.

4.2.2. Ownership Structure and OMA Performance

Ownership structure can influence OMA performance too. Xu & Wang (1999) investigate ownership structure of publicly listed companies in China within the framework of corporate governance. They find profitability of Chinese firms is either negatively correlated or uncorrelated with government ownership. They attribute this to the inefficiency of public control. Wei, Xie & Zhang (2005) exam the relation between ownership structure and firm value across a sample of China's partially privatized, former state-owned enterprises (SOEs) from 1991-2001. They find that state and institutional shares are significantly negatively related to firm value. They also find that foreign ownership is significantly positively related to firm value. They argue that the agency problem is relatively more severe in many emerging markets due to the absence of strong legal protections and other governance mechanisms. Managers/insider stock ownership in China is minimal and insiders can gain control either through direct government appointments or indirect political influence.

4.2.3. Other OMA Determinants

Research on OMA determinants has focused on three categories of determinants. Many studies find that transaction details, such as method of payment (Jensen & Meckling, 1976), industry relatedness (Doukas & Lang, 2003), and professional advisors (Lowinski et al., 2004) affect OMA performance. Other studies highlight bidders' endowment factors: such as firms' capabilities of internalization (Nocke & Yeaple, 2007);[66] firm size and book-to-market ratio (Gugler et al., 2002; Sudarsanam & Mahate, 2003); and associated ownership characteristics (Boubakri et al., 2008; Morck et al., 2008). A third set of determinants relate to the target

[66] As proxied by the firm's listing market in this chapter.

location: such as country-specific endowments (Kogut, 1985); cultural distance (Larsson & Finkelstein, 1999); host county's growth rate (McDonald, 2001); and exchange rate volatility (Dewenter, 1995) with the host country. Buckley et al. (2007) investigate the determinants of Chinese outward direct investment. Their results support that political risk, cultural proximity and host natural resources endowments significantly affect OMA performance.

4.2.4. Different Targets, Different Drivers for Short- and Long-run M&A Performance

In the weak form of efficient markets, short term investors respond quickly to events in the light of available information and rational anticipation. In the long run, overreaction to information is about as frequent as post-event reversal. Fama (1998) concludes that market efficiency survives the challenge from the literature on long term return anomalies. Although individual bidders or targets might behave diversely, return anomalies tend to disappear over longer horizons.

Apart from market efficiency theory, there are numerous international finance management theories explaining the drivers of overseas M&A performance. Failure to achieve managerial synergy has been identified as a severe problem in overseas transactions (Larsson & Finkelstein, 1999). Differences in the cultural backgrounds of bidders and targets can destroy firm value (Buckley & Casson, 1976; Morosini et al., 1998). Level of political risk in the host countries, including exchange rate variation (Cebenoyan et al., 1992) or changes in economic policies in the home or host countries, can generate huge volatility in long term performance. All of these are difficult to reliably predict into the post merger period.

Doukas & Lang (2003) find that the performance of short- and long-run green field investment depends on the extent of geographic and industry diversification. O'Regan & Ghobadian (2004) argue that improvement of short and long term performance is affected by strategy, leadership, culture and organizational efficiency variables. Short-term performance is "internally orientated" while long term performance is more likely to be "externally orientated". Zero2IPO Research Center (2010) reports that short- and long-term M&A performance of Chinese listed firms frequently diverge. Insignificant short term performance is followed by positive long term performance.

Indeed, it is questionable whether short- and long-run performance of Chinese OMAs is determined by the same factors. For example, government policies may target, not profitability, but many other strategic concerns such as energy security or industry restructuring (Dunning & Lundan, 2008). This may lead to negative short-run returns but positive long-run performance. On the other hand, SOEs might fail to achieve shareholders' expectations due to their inefficient management mechanisms (Wei et al., 2005).

In all, different targets, different drivers lead to different OMA performance. We therefore expect the long-run determinants of Chinese OMA performance to be different from their short-run performance.

4.3. Data

We investigate Chinese acquirers' stock performance one and three years after their OMA effective dates. We include the Chinese mainland, Hong Kong and US stock exchanges in our analysis. Our sample consists of completed Chinese OMAs effective between January 1st, 1992 and December 31th, 2008. We apply the Calendar-time approach using monthly returns as calculated according to their adjusted prices.[67] We delete observations with more than 50% zero returns in the 0-41month observation period. Our sample includes some shares that are listed on more than one market. When this happens, and when we need to choose only one

[67] We apply the following formula for stock returns: $\ln(P_t / P_{t-1})$. Please see Brown & Warner (1985) and Norman (1992) for details.

listing, we select the share with the highest-trading volume. In the event that a security has a larger market capitalization but a smaller trading volume, we select the security with highest market capitalization if its market capitalization is at least two times larger.

4.3.1. Firm Size and BM Ratio

Firm size is measured by market capitalization on the effective date.[68] Book to market ratio (BM) is calculated using end-of-the-fiscal year book values for the year preceding the effective date. Market values are calculated six months prior to the effective date. We note that shares listed on different markets have different fiscal years. The end of the fiscal year for Chinese mainland market is December 31st. The fiscal year end dates for the Hong Kong and US markets are March 31st and September 30th, respectively. We use the appropriate fiscal year book value depending on the market in which the security is listed.

In calculating the small minus big variable for use in the Fama-French 3 Factor model (FF3FM) we use largest median firm size in the HK market to categorize small- and big-sized firms for the return portfolio of small minus big (SMB).[69] For calculating the high minus low variable, we divide firms into three BM ratio categories: those having BM ratios in the (i) highest 30%, (ii) middle 40%, and (iii) lowest 30% groups. We then calculate the portfolio return as the ratio of returns from the highest 30% over the lowest 30%.

4.3.2. Market Return

For the purposes of calculating market returns, we used the Shanghai Composite Index, Hang Seng Index and S&P 500 Index for the three markets (following the same procedure we

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[68] Effective date is the date when M&A transactions are officially completed.

[69] In Fama and French (1992,1993), they allocate size portfolios based on NYSE breakpoints although stocks in AMEX and NASDAQ are included in their sample. They argue that if they used stocks from all three exchanges (NYSE, AMEX and NASDAQ) to determine the size breakpoint, most portfolios would end up with only small stocks. For the same reason, we allocate our size portfolios based on HK listings in our sample, where largest market value locates among the three listings (Chinese mainland, Hong Kong and U.S.). Please note market equity (market value) of U.S. listings in our sample are ADRs and have smaller market value comparing to mainland or Hong Kong listings.

used for the event time approach). We also tried using the MSCI world index as a common market proxy.

4.3.3. Risk Free Rate

A common approach for estimating the risk free rate consists of using the 1-month or 3-month T-bond. However, we could not find 3-month T-bond until year 2008 for the China mainland. Nor could we find T-bond assets for the Hong Kong market. To make risk free rates in the three markets comparable, we choose the China 1 year time deposit, the 1 year Hong Kong Dollar interest rate, and the annualized US Federal funds rate, respectively. These were converted to monthly rates by dividing by 12.

4.3.4. Firm Survivorship and Data Availability

Our investigation covers a three-year period. Accordingly, we rebalance market capitalization and BM ratios of firms for each year of the sample. Firms delisted from the stock exchanges during the analysis period are removed. We omitted all firms for which DataStream did not maintain data relevant for calculating the BM ratio or market capitalization for portfolio grouping.

4.4. Methodology

4.4.1. Long Term Performance Estimator

The Calendar-time approach is a popular estimation procedure for calculating long term performance. The Fama-French Three Factor Model (FF3FM) is widely used in calendar-time approach (Fama & French, 1992; Fama & French, 1993).

Fama & French (1993) note that when excess market return is the only explanatory variable in time series regressions, the intercepts for stocks include both the size and BM effects. The intercept for the smallest portfolios exceed those for the biggest by approximately 0.22%-0.37%; in every size quintile, the highest BM quintile exceed those for the lowest by 0.25%-0.76%. When three factors (market excess return, SMB portfolio return and HML portfolio return) are included in the regressions, the intercepts were pushed from strong positive values towards 0, which reveals that three factors absorb common time-series variation in returns and do a good job explaining the cross-section of average stock returns.

In the three-factor regressions in Fama & French (1993)--reproduced in Table 5A, the βs for the smallest-low BM and biggest-high BM are 1.04 and 1.06 respectively. These compare to 1.40 and 0.89 in the univariate regressions. This indicates that the addition of SMB and HML to the regression pushes the βs towards 1.0; low βs move up towards 1.0 and high βs move down. Fama and French argue that this behavior is due to correlation between market returns and SMB and HML. Further, Fama & French (1993) find that R^2s are much higher in three factor regressions compared to one-factor and two-factor models, The average R^2 in FF3FM is larger than 0.93. (See Table 5A for details.)

Some studies simply regress abnormal returns over time on an intercept term (Eberhart et al., 2004; Ivkovich et al., 2006). Others estimate calendar-time abnormal returns (CTAR) or so-called mean monthly abnormal return (MMAR). The FF3FM is taken as the benchmark model to get expected returns. CTAR is calculated as the difference between actual and expected returns. After analyzing various methods to test for long-run abnormal stock returns, Lyon, Barber, & Tsai (1999) recommend CTAR as a reliable procedure for investigating long term performance.

Mitchell & Stafford (2000) employ CTAR to test performance of M&As, seasoned equity issues, and equity repurchases in US markets during July 1961 to December 1993. They find negative, 3-year CTARs in M&A activities for all control groups except value firms. Byun & Rozeff (2003) study 1-year CTARs after 12,747 stock splits in the US from 1927 to 1996. They find small or negligible 1-year CTARs, except for subsamples of 2-1 splits. Savor & Lu

(2009) find significant and insignificant negative, 3-year CTARs for US stock acquirers and cash acquirers, respectively, in 1978-2003.

4.4.2. Long Term CTAR

We measure post-OMA long-run performance using calendar-time abnormal returns. Fama and French (1992) find that along with beta, firm size and book-to-market ratio are statistically significant in explaining returns. We use the Fama-French (1993) three factor model (FF3FM) to evaluate abnormal returns in the sample:

(1) $$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) - s_i SMB_t - h_i HML_t$$

where R_{it} is observed returns for security *i* in month *t*,

R_{ft} is risk-free rate in month *t*,

R_{mt} is observed market return in month *t*,

SMB_t equals the small minus big mean return in month *t*, a "size" factor;

HML_t represents the high minus low mean return in month *t*, a "book-to-market" factor.

Note that $(R_{mt} - R_{ft})$ measures the market risk premium and $(R_{it} - R_{ft})$ measures abnormal returns. *t* is measured in months.

To generate size and book-to-market factor values, we create six portfolios by splitting the firms in two size groups and in three book-to-market groups. The high book-to-market portfolio consists of the 30% of stocks with the highest book-to-market ratios in a given year. The low book-to-market portfolio consists of the 30% of stocks with the lowest book-to-market ratios. The groups of small and big firms break at the median of firm market value on the effective date.

We estimate the FF3FM of equation (1) to get estimates of coefficients, α_i, β_i, s_i, and h_i. We calculate monthly calendar-time abnormal returns (CTARs) according to the following formula:

(2) $CTAR_{it} = R_{it} - E(R_{it})$; where

(3) $E(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i (R_{mt} - R_{ft}) - \hat{s}_i SMB_t - \hat{h}_i HML_t$

where $\hat{\alpha}_i, \hat{\beta}_i, \hat{s}_i, \hat{h}_i$ are obtained by estimating Equation (1) as described above.

We aggregate monthly CTARs, average across securities and report their long-run performance over a three-year horizon. The associated t-stat for long-run performance is given by:

(4) $$t = \sqrt{\frac{N}{T}} \times \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} CTAR_{it}}{\sigma_t};$$

where T indicates the months aggregated, N refers to securities involved, and σ_t is the standard deviation of CTAR$_t$. Note that Equation (4) is analogous to $Z_{Interval}$ in Chapter Three. Note further that the standard deviation represents an in-sample standard deviation as there are not separate “estimation” and “test” periods. In order to calculate more reliable coefficient estimates, we divide our sample into 16 portfolios due to their firm size (4 groups) and BM ratio (4 groups). Equation (1) is then estimated separately for each subsample. These coefficients are then used to calculate expected returns, $E(R_{it})$.

4.4.3. Determinants of Chinese OMA

There are many factors involved in overseas M&A performance. The complexity of their interrelationships makes it difficult to select representative explanatory variables that are not highly correlated with each other. Our approach is as follows.

Following the organization of the established literature (see above), we categorize the explanatory variables into three groups:

(1) M&A transaction details. These variables include information on transaction value, method of payment, related takeover, target's attitude (as in hostile or friendly), number of bidders, professional advisor involvement, etc. Because there are no competitors in the bidding and all the takeovers in our sample are friendly takeovers, we use the variables INDREL (related takeover), CASH (cash only payment), LNTRAVALUE (transaction value) and ADVISOR (professional advisor dummy) to represent the factors associated with M&A transaction details.

(2) Target location. These variables include variables that measure firm and market characteristics associated with the target and acquiring firms. The variables CULDIS (cultural distance between bidders and targets), FEX (change on exchange rate), DEVDC (dummy variable indicating target is from a developed country) and THK (HK targets) all belong to this group.

(3) Bidders' endowment. These variables include LNMV24A (bidders' firm size), Y2BM (book-to-market ratio) and dummy variables to identify the listed market.

We also include variables that are specific to our Chinese sample. China is an emerging economy. Most of the Chinese firms are not expected to achieve competitive power in the market place. To some extent, the Chinese OMA wave might represent strategic decisions made at the government, rather than firm, level. Government impact could be an important driver of OMA transactions. Therefore, we also include variables that measure the influence of government. These are GOVTOWN (dummy variable indicating the enterprises is government-owned) and POLICY (a dummy variable indicating the OMA event occurred during the years 2002-2008). It is very clear from a listing of Chinese OMA events that 2002 seems to be a break point for both the number of OMA deals and their transaction value.

Both of these increase dramatically after 2001. The Chinese government initiated its "Go Global" policy in the year 1999. Further, China became a WTO member in 2001. These two policy events are the likely causes of the subsequent spark in OMA deals and values. The variable POLICY is designed to capture the influence of these policy events.

Another consideration unique to our sample, is that many of the firms list across different markets: the Chinese mainland markets, the Hong Kong markets and US markets.[70] Yun, Abeyratna, & David (2005) argue that stock returns in different nations are unlikely to be highly correlated. To capture persistent differences that may exist across these markets, we include market dummy variables. Finally, Mitchell & Mulherin (1996) argue that firms' performance is distinctively different among sectors. Therefore, we also include industry dummy variables to capture differences across sectors.

We employ the following models to investigate determinants of the 3-year performance (Y3CTAR) of Chinese OMAs. All models include the variables for government ownership and book to market ratios (GOVTOWN and Y2BM) because preliminary analyses identified these as robust determinants of OMA performance.

Model 1 includes all variables:

Model 1

$$\begin{aligned} Y3CATR &= \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 CULDIS + \beta_4 FEX + \beta_5 DEVDC \\ &+ \beta_6 THK + \beta_7 INDREL + \beta_8 CASH + \beta_9 LNTRAVALUE + \beta_{10} ADVISOR + \beta_{11} LNMV24A \\ &+ \beta_{12} HKM + \beta_{13} USM + \beta_{14} ITIN + \beta_{15} POLICY + \varepsilon \end{aligned}$$

Model 2 includes all the variables of Model 1 but omits the POLICY variable.

Model 2

$$\begin{aligned} Y3CATR &= \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 CULDIS + \beta_4 FEX + \beta_5 DEVDC \\ &+ \beta_6 THK + \beta_7 INDREL + \beta_8 CASH + \beta_9 LNTRAVALUE + \beta_{10} ADVISOR + \beta_{11} LNMV24A \\ &+ \beta_{12} HKM + \beta_{13} USM + \beta_{14} ITIN + \varepsilon \end{aligned}$$

[70] We delete all bidders listing other than mainland, HK or US to control the variation of their stock returns.

Model 3 focuses on target location variables.

Model 3

$$Y3CTAR = \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 CULDIS$$
$$+ \beta_4 FEX + \beta_5 DEVDC + \beta_6 THK + \varepsilon$$

Model 4 focuses on the long-run effect of Go Global

Model 4

$$Y3CTAR = \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 POLICY + \varepsilon$$

Model 5 focuses on variables associated with M&A Transaction Details

Model 5

$$Y3CTAR = \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 INDREL$$
$$+ \beta_4 CASH + \beta_5 LNTRAVALUE + \beta_6 ADVISOR + \varepsilon$$

Model 6 focuses on Bidder's Endowment variables

Model 6

$$Y3CTAR = \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 LNMV24A$$
$$+ \beta_4 HKM + \beta_5 USM + \varepsilon$$

Model 7 pays special attention to possible performance issues associated with the government's strategic interest in the high technology and natural resource industries.

Model 7

$$Y3CTAR = \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \beta_3 ITIN + \beta_4 NATRES + \varepsilon$$

Model 8 is a bare-bones model that focuses on the two robust determinants of OMA performance.

Model 8

$$Y3CTAR = \alpha + \beta_1 GOVTOWN + \beta_2 Y2BM + \varepsilon$$

4.5. Results

Tables 4.1 through 4.3 report the distribution of OMA deals by year, country, and industry. These are similar to the distributions reported in Chapter 3. However, since this chapter is concerned with long-run performance, and sufficient 3-year time series data is unavailable for deals effective after December 31, 2008, there are fewer observations.

Table 4.3 shows that both the number of deals and the OMA activity increased substantially in the average transaction value increased dramatically in many of the sectors after 2002.(i) Telecommunications and Electronics, Prepackaged Software, (ii) Energy and Natural Resources, and (iii) Miscellaneous Business Services sectors.

4.5.1. Long Term Performance of Chinese OMAs

Table 4.4 reports the long-term performance of Chinese OMAs at six-month intervals. Six months after the effective date, Chinese acquiring firms experienced, on average, abnormal returns of 5.41%. Over time, these positive abnormal returns dissipated. After three years, Chinese acquiring firms experienced a cumulative abnormal return of negative 1.46%. However, none of the CTAR are statistically different from zero.

Fama and French (1993) apply U.S. stock markets data to test their three factor model. Table 4.5A reproduces results from their Table 4.6 and 4.9. The main points of these tables are:

1. Beta, SMB and HML factors are statistically significant in all 25 portfolios;
2. Beta coefficients are close to one;
3. The loadings of SMB factor decline monotonically as the size quintile gets larger (within the same book-to-market quintile), indicates higher risk premium for small sized firms;
4. The loadings of HML factor increase monotonically as the book-to-market ratio gets larger (within the same size quintile), indicates higher returns for higher book-to-market ratio firms (value firms);
5. The abnormal return “alphas” in FF3FM appear insignificant.
6. FF3FM fits well with all very large R-squares in each of the 25 portfolios;

However, when they apply a related model to international markets (two-factor model, beta and book-to market ratio), they find the multi-factor model does not work as well for emerging markets (Fama & French, 1998).

Table 4.5B reports our results of estimating the FF3FM (see Equation 1) for each of the sixteen portfolios. The dependent variable is observed, excess monthly returns for security *i* at time *t*. The independent variables are market excess returns for security *i* at time *t*, SMB portfolio return at time *t* and HML portfolio return at time *t*.

We get mixed results in Table 4.5B. Fourteen of the sixteen Beta coefficients are insignificantly different from one. We do find some evidence that SMB and HML factors provide additional explanatory power. Three out of sixteen SMB coefficients and four out of sixteen HML coefficients are significant at the 5% level. In general, loading of firm size factor (SMB) decline as the size quintile gets larger (within the same book-to-market quintile) - though the change is not monotonic. The leverage factor (HML) results are not as favourable. Their loadings increase as the book-to-market ratio increases for two of the sixteen portfolios - but again the effect is not monotonic. Nine of the sixteen intercepts (alphas) are insignificant. Finally The R-squares are reasonably high although they are somewhat lower than Fama and French (1993). In all, our results are not as strong as Fama and French (1993), but they are generally supportive of the FF3FM, given the relatively small sample size on which the results are based.

4.5.2. Short- and Long- term Variation

OMA performance is broken down by year in Table 4.6. OMAs announced in 1997 registered the highest wealth effect of 14%, followed by 4% in 1996. For 3-year, long term performance, OMAs announced in the year 2007 achieved the highest abnormal return of 16%. The largest three year loss was associated with deals made in 1998. There is also an interesting divergence in short- and long-run OMA performance in the pre- and post- Go Global periods. OMAs before 2002 generally achieved higher short run abnormal returns (CAR [-1,1]) than those from 2002 afterwards. In contrast, long term abnormal returns

(CTAR) went in the opposite direction. Mean and median CTARs for the years 2002-2008 are generally higher than for earlier years.

4.5.3. Performance Differences in Segmented Markets

Table 4.7 reports OMA performance across the three markets (Chinese mainland, Hong Kong and US). A total of 182 observations are included in the three listed markets, with 50 securities listed in the Chinese mainland markets; 68 in Hong Kong and 64 in U.S. markets. While there are notable differences across the markets, none of the CTAR values are significant, or even close to being significant.

4.5.4. Sector Performance and Interaction with Industry Restructuring

We next explore long-run performance by industry. Chinese OMA performance varies across industries during the 1994-2008 period (see Table 4.8a). The greatest short-run performance (CAR [-1,1]) is achieved in the Wholesale and Retail Trade sector (16%), followed by Miscellaneous Manufacturing Products(3%). After three years, the highest-performing OMAs were those in the Miscellaneous Business Services (18%), Energy and Natural resources (8%), and Miscellaneous Manufacturing Products (5%). Abnormal returns were especially volatile for the Wholesale and Retail Trade sector. The largest short-run returns (10%), and also the lowest long-run returns (-27%, 2-year CTAR) were observed in this sector.

We use regression analysis to determine whether the industry differences noted above are statistically significant. Table 4.8b reports the results of regression analysis where the dependent variable is the respective performance measure (CAR [-1,1], 1-year CTAR, etc.) and the explanatory variable is a single dummy variable for the respective sector. For example, we find that the Telecommunications and Electronics, Prepackaged Software industry experienced short-run abnormal returns that were 1.17% lower than other industries. However the difference was not statistically significant.

The only significant differences are those associated with the Wholesale and Retail Trade sectors. This industry experienced significantly greater returns in the short-run (CAR[-1,1]) and significantly lower returns in the long-run (1-year CTAR, 2-year CTAR). We hypothesize that the lowering of trade barriers as a result of China joining the WTO had particularly negative effects on the trade sector, as foreign imports chipped away at previously monopolistic trade markets.

We note that while these results are suggestive, they ignore the influences of other determinants of Chinese OMA performance. We further investigate industry differences later in this chapter when we control for the influence of other variables.

4.5.5. Top OMA Deals and Performance

Table 4.9 reports the top 15 Chinese overseas M&As in transaction value during the 1994-2010 period. The top Chinese OMA deals cluster in the energy and natural resources sectors. We report both short- and long-run performance in the table. Four-fifths of the deals achieve positive CTARs after three years. Most of them employed foreign professional advisors. Of these, Goldman Sachs has the most successful record. All six of the OMA deals they advised achieved positive long term performance. In contrast, deals that Lehman Brothers advised did poorly.

Take Top 1 Chinese OMA Deal in Table 4.9 as an example. CNPC announced to acquire PetroKazakhstan 100% shares on October 26, 2005. With cash payment 55 USD per share, the total transaction value was as high as 4141.2 million USD, listing the largest Chinese OMAs so far. PetroKazakhstan is an integrated international energy company with upstream and downstream operations covering oil and gas exploration, development, refining and marketing of refined products. It is also Kazakhstan's second-largest foreign petroleum producer, and the largest manufacturer and supplier of refined products. It is an UK-based firm according to SDC Platinum M&A database. However, because it is registered in Canada, many researchers consider it a Canadian-based firm.

PetroKazakhstan evidenced an excellent performance in oil exploration, oil and gas development and production, crude processing, transportation and sales of refined products, HSE, and operational management in 2006, 1 year after the OMA transaction. Crude oil production of 10.5 million tons and crude runs of 4.03 million tons were achieved, the highest levels ever in the company's history. On December 2010, the First Phase of the Third Zhanazhol Oil & Gas Processing Plant was completed and became operational.[71]

According to our research, the acquirer didn't achieve positive abnormal returns at the announcement. The markets responded -2.5% abnormal return in (-1, 1) interval, which implies less confidence to the Chinese OMA in the market place. However, three years after, CNPC shareholders finally gain 12.4% abnormal return in stock markets, which indicates the Chinese acquirer (CNPC) benefits from the strategic OMA activities and the OMA event generates synergy effect after the acquisition.

[71] Information from CNPC website: http://www.cnpc.com.cn/eng/cnpcworldwide/euro-asia/Kazakhstan/

4.5.6. Chinese OMA Performance Determinants

The final stage of our analysis uses multivariate regression to estimate the determinants of Chinese OMAs. Table 4.10 defines the variables used in the analysis. As discussed above, we include:

1. Government impact variables: government owned enterprises (GOVTOWN) and policy dummy (POLICY)
2. Industry restructuring variables: high technology sector (ITIN) and natural resources sector (NATRES) [72]
3. Target location variables: cultural distance with targets (CULDIS), U.S. dollar depreciation against Chinese RMB (FEX), HK targets (THK) and developed targets (DEVDC) [73]
4. Acquirers' endowment: acquirers' firm size, book-to-market ratio and acquirers' listing markets[74]
5. Transaction details: related industry, cash only payment, deal value and professional advisor involvement

Table 4.11 reports summary statistics for the respective variables. The mean short-term abnormal return (CAR [-1,1]), 1-year, 2-year and 3-year Calendar-time abnormal returns (Y1CTAR, Y2CTAR and Y3CTAR) are 1.3%, 5.2%, 2.8% and -1.46% respectively. The average cultural distance is 1.29. The positive, mean FEX value indicates that the Chinese RMB was appreciating against the USD over 1994-2008. 75.4% of the deals involve

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[72] These two sectors are included in industry restructuring because many researchers argue that Chinese OMAs in these sectors are less likely for efficiency-seeking but Chinese government strategy of industry restructuring and economy security.

[73] Although high correlation between developed targets and HK targets are expected, we think it is still necessary to look at HK targets impact because 40% of the total targets and 54% of developed ones are from HK in our sample.

[74] We apply 1 year lag firm size and book to market ratio data here, which means to regress year 3 abnormal returns on year 2 firm size and book-to-market ratio under the assumption that investors make future investment decision according to exist information.

developed targets. HK targets constitute 40.2% of Chinese OMAs. Half of the deals involve targets in related industries; and half of the acquirers are government-owned enterprises. 73.8% of the deals are initiated in the Go Global years. 54.1% of the deals are cash payment only. 25.4% of them are natural resources targets, 33.6% are hi-tech targets. The average transaction value of Chinese OMAs in the sample is 278.1 million US dollars, while the mean market value (firm size) of acquirers is 20715.6 million USD. The average acquirers' book to market ratio is 0.56 and 29.5% of the acquirers employed professional advisors. About 42% of the acquirers list in Hong Kong, and 19% list in U.S.

The correlation matrix in Table 4.12 finds one correlation coefficient higher than 0.5 in absolute value. The variables CULDIS and THK have a simple correlation of -0.7. This is not surprising given that Hong Kong and the Chinese mainland share a largely common culture.

Table 4.13 reports the univariate regression results relating the determinants of long-run OMA performance. It reveals that CAR (-1,1) is significantly, negatively correlated with the previous year's CTAR. Y1CTAR and Y2CTAR are significantly correlated with the appreciation of Chinese RMB. We find a significantly negative correlation between yearly CTARs and developed targets. Y3CTAR is positively and significantly related with industry relatedness (INDREL) and having a target in the natural resources sector (NATRES). Yearly book-to-market ratios are significantly negatively correlated with Y1CTAR and Y3CTAR. Listing market and employment of a professional advisor are significantly correlated with Y1CTAR, but not subsequent CTARs.

Table 4.14 presents the multivariate regression results. While a number of the variables are significant in any one regression, only two variables are consistently significant in all the regressions in which they appear (GOVTOWN and CULDIS). Government-owned acquirers have 3-year abnormal returns that are 10-22% lower than public firms. Further, the greater the cultural distance between acquirers and targets, the lower are 3-year abnormal returns.

4.6. Conclusion

In this chapter, we apply the calendar-time approach to investigate Chinese long-run OMA performance. We find that long-run abnormal returns are insignificantly different from zero. This finding generally holds across all listing markets and industry sectors.

We also investigate the influence of a large number of potential determinants of long-run performance. Not surprisingly, we find that cultural distance is a significant determinant of OMA success. Long-run profitability is likely to be positively and significantly impacted when acquirers and targets share common cultural values. We note that this significant relationship remains even when we have a separate variable for Hong Kong targets.

A main finding of ours is that the long-run performance of Chinese OMAs is negatively associated with government ownership. Firms that are government-owned are likely to experience three-year abnormal returns that are 10 to 22 percent lower than public firms. State-owned enterprises (SOEs) start from a position of monopoly power in Chinese domestic markets. We speculate that investors are not confident that SOEs can maintain their market power when going abroad. Secondly, SOEs are more likely to initiate strategic investments that pursue government objectives at the cost of shareholders' interests. With this in mind, investors may prefer OMA acquirers with more private ownership.

Buckley et al. (2007) note that Chinese SOEs benefit from soft capital constraints and potential government guarantees in domestic financial markets. But too much cash flow can motivate inefficient OMAs. Furthermore, as enterprises from an emerging market, most Chinese acquirers do not have much international operations experience. Stimulated by the national Go Global policy, overconfident Chinese managers may overvalue targets and overestimate the creation of synergistic value. These negative consequences of being government-owned work against the positive advantages of government control. Ultimately, it is an empirical question which one dominates. Our analysis indicates that, at least in the Chinese context, markets have determined that the bad outweighs the good.

Chapter Five Using Multiple-Listing Information in Event Studies

--*Application to Chinese Overseas Mergers and Acquisitions*

In an event study, we evaluate stock market returns according to economy-wide or firm-specific events. Sometimes the sample firms have their common equities listed in more than one market. In most research, the corresponding home market equity, or equity from the most liquid market, is selected in investigating abnormal returns. The question arises as to which is the most appropriate market (or markets) to use for the purpose of estimating abnormal returns. The question becomes far more interesting in segmented market environments. For example, emerging markets may be segmented from developed ones and arbitrage activity across these markets may be restricted in some way. This implies that there may be substantial price deviations, with low return correlations. Estimating abnormal returns from just home listings or "most liquid" listings potentially throws away valuable information. On the other hand, indiscriminate pooling is likely to count the same information more than once. Therefore, in this chapter, we try to solve the problem of (i) pooling all multiple listings in the sample, and (ii) "weighting" individual listings by the new information they provide, so as to produce consistent and asymptotically efficient estimates of abnormal returns. We apply this new approach to estimate wealth effects of Chinese OMAs, using multi-listings of Chinese acquirers.

5.1. Introduction

Event studies have become the predominant methodology for determining the effects of an event on the distribution of security returns. The hypothesis is that information shocks affect average stock returns, across firms with similar information arrivals. Initially, event studies were applied to single-country, developed markets.[75] Recently they have been extended to multiple countries and/or emerging market settings (Aybar & Ficici, 2009; Campbell, Cowan, & Salotti, 2010). While this opens up opportunities for researchers, it also raises statistical issues associated with the properties of cross sectional returns.

In this chapter, we discuss the extension to multi-listings of the same asset in multiple markets in event studies. The standard event study estimates the average abnormal returns of securities subject to the event of interest. The question arises as to which is the most appropriate market (or markets) for the estimation when some of the securities have their shares listed in more than one market. The most common approach is to use returns from each firm's home market (Aktas, de Bodt, & Roll, 2004; Bailey, Karolyi, & Salva, 2006; Doidge, 2004; Faccio, McConnell, & Stolin, 2006; Kim, 2003; Wang & Boateng, 2007). Others use returns from the firm's most liquid markets (Aybar & Ficici, 2009; Baruch, Karolyi, & Lemmon, 2007; Campbell et al., 2010).

The underlying theory of these approaches is based on the price discovery literature on cross-listings and market liquidity. There exists no consensus whether home- or foreign-listing contributes more to price discovery. Some studies suggest that home markets play the dominant role (Chen, Li, & Wu, 2010; Grammig, Melvin, & Schlag, 2005; M. Kim, Szakmary, & Mathur, 2000; Lieberman, Ben-Zion, & Hauser, 1999; Pascual, Pascual-Fuster, & Climent, 2006). Yet, evidence from other studies lends support for a significant role for

[75] Please see Chapter Two Literature Review for details.

foreign listings in price formation. This appears to be especially the care in high liquid markets, such as US markets (Chan & Subrahmanyam, 2005; Ranaldo, 2001). These studies argue that US markets have "spill over" effects on price discovery in other exchanges in the world (Eun & Sabherwal, 2003; Lau & Diltz, 1994; Werner & Kleidon, 1996).

Liquidity has long been considered an important variable affecting the prices of financial assets. The higher liquid of a given asset should be reflected in a higher price or a lower required return. However, the multidimensional nature of market liquidity makes it a tricky exercise to determine the highest liquid market in multiple market settings. The usual approach consists of breaking up liquidity into three components: tightness, depth and resiliency. Trading volume is regarded as a standard measure for market liquidity (Baruch et al., 2007; Chan & Subrahmanyam, 2005). But Ranaldo (2001) surveys nine liquidity proxies and argues that market depth, trading time and intraday bid-ask spread are also important dimensions of market liquidity, and critical components for price discovery.

On the other hand, stock markets differ by investor protection, industry or ownership concentration, market liquidity, accounting standards or regulation. Different market characteristics can affect the statistical properties of stock returns. Mikkelson & Partch (1986) and Patell (1976) develop a parametric test based on standardized returns for better OLS estimation. Brown & Warner (1985) argue that event study methodologies based on OLS estimation of the market model and standard parametric statistics are well-specified even with non-normal and heteroscedastic return errors. However, the data they used in their simulations are from US markets (from the CRSP database). They do not discuss the situation when markets in diversified nations are pooled in the sample construction. Boehmer, Masumeci, & Poulsen (1991) develop a variance-change correction procedure, called the standardized cross-sectional test and Campbell et al. (2010) apply this test to non-US stocks. However, their approach reports point estimates and inference results according to standardized residuals instead of non-transformed residuals. In other words, they report standardized abnormal returns and corresponding hypotheses tests, rather than the non-transformed average abnormal returns.[76]

One feature common to these approaches is that they use single-listed observations in the estimation of abnormal returns. Presumably this reflects an assumption of semi-strong market efficiency. With unrestricted arbitrage across markets, inter-market price deviations will be small and transitory, rendering the choice of listing irrelevant to abnormal returns estimation. In other words, unrestricted arbitrage activity ensures that all listings of a firm's securities quickly reveal the same information. 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 several studies support the price parity view for developed markets (Eun & Sabherwal, 2003; Grammig et al., 2005), more recent work, which typically includes data from emerging markets, often discovers significant deviations from price parity (Blouin, Hail, & Yetman, 2009; Gagnon & Karolyi, 2004). 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.

Together, these results cast some doubt on the usual event-study practice of using returns from a single listing for each firm. Our approach is to aggregate cross-listings instead. According to our investigation in DataStream, 33.47% of active entity securities in the world markets are multi-listings. Put another way, including multi-listings allows one to increase

[76] Please see 5.2.3. for details.

sample size by 57% (=88,631/56,477).[77] Thus, it increases sample size, which can be an important consideration when undertaking event studies in emerging markets.

Further, investors in different markets possess different information sets. Left to their own devices, they may respond differently to a given event. If arbitrage is unable to aggregate these multiple responses, then the use of single-listing yields abnormal return estimates that are incomplete in the sense that they ignore important information embedded in the price responses observed in other markets. In such circumstances, using returns from all markets in which each firm's securities are listed enable "full-information" abnormal return estimations to be obtained.

However, pooling of multi-listing data involves not only non-constant variance but also cross-sectional dependence unless markets are fully segmented.[78] The more integrated the markets, the higher the cross-sectional correlations. Brown and Warner (1980; 1985) discuss "clustering" in calendar and industry results, which can bias hypothesis testing. Multi-listings can exacerbate "clustering" in returns. When market model residuals are positively correlated with each other via multi-listings, such clustering will increase the variance of the performance measures. If the estimation procedure ignores this clustering, the null hypothesis will be rejected too frequently when multi-listed returns are positively correlated. What is required is a method that adjusts for both heteroscedastic errors and

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[77] Among the 88,631 active equity listings (which include ADRs and GDRs), there are a total of 56,477 firms, and 18,904 of these firms multi-list (which could include listings in the same market, more on this later, but still valid for our analysis).

[78] We suspect the integration of world markets. Cho, Eun,& Senbet (1986) provide an empirical investigation of the arbitrage pricing theory in an international setting. The results reject the joint hypothesis that international capital market is integrated. Griffin (2002) examines whether country-specific or global version of Fama and French's three-factor model better explain time-series variation in international stock returns. Although the author focuses on markets that are likely to be integrated (U.S., UK., Canada and Japan), the results indicate that the model is better performed on country-specific basis than global version, which implies market segmentation. Even domestic markets in one country are not integrated. Hietala (1989) finds partially segmented market in Finland. The domestic securities are lower priced by their local citizens than foreign investors. Hung-Gay, Wai, & Wai Kin (2000) report the latent risk premiums for the A and B shares in China are only weakly correlated, which implies the two markets reflect different fundamental forces and partially segmented.

correlated returns due to multi-listings. In other words, the estimation procedure should extract the independent information from each listing while counting the common information only once.

In this chapter, we outline a simple procedure that achieves this objective while producing consistent and asymptotically efficient estimates of abnormal returns. In the next section, we describe this "generalized" approach in detail. In section 3, we illustrate its use by applying it to a sample of foreign mergers and acquisitions by Chinese acquirers. Section 4 provides some concluding remarks.

5.2. A generalized Methodology for Extending Event-study Analysis to The Case of Multi-listings

5.2.1. The Standard Case: Single-market Listing of Securities (Error are homoscedastic and cross-sectionally independent)

Consider initially the data generation process (DGP) under the benchmark case where all firms in an event data sample are listed on a single exchange. This is the situation envisaged in standard event study analysis. We briefly outline the mechanics of that analysis in order to facilitate extension to the more general multiple-listing case considered below.

Let AR_{it} denote firm *i*'s abnormal return on day *t* of the test period, *i* =1,…, N and *t*=1,…,T. That is,

(1) $AR_{it} = R_{it} - \hat{R}_{it}$,

where R_{it} is the observed return during the test period, and $\hat{R}_{it}$ is the predicted return based on data observed during the pre-test period of length S. We assume the AR_{it} are independent and normally distributed with a mean of 0 and a standard deviation σ. Let the DGP associated with individual AR_{it} observations be given by the following equation:

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

where

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

In this case, the OLS estimate of β, $\hat{\beta}_{OLS}$, is efficient. $\hat{\beta}_{OLS} = \boldsymbol{(x'x)^{-1} x'y}$. It is easily shown that

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

where AAR_t is the "average abnormal return".

If σ^2 is known, then $Var(\hat{\beta}_{OLS}) = \sigma^2 \boldsymbol{(x'x)^{-1}}$, and $s.e.(\hat{\beta}_{OLS}) = \sqrt{\sigma^2 \boldsymbol{(x'x)^{-1}}}$. The latter is easily shown to be equivalent to $s.e.(\hat{\beta}_{OLS}) = \frac{\sigma}{\sqrt{N}}$. To test the null hypothesis that $\beta = 0$, one forms the Z statistic, $Z_t = \frac{\hat{\beta}_{OLS}}{s.e.(\hat{\beta}_{OLS})} = \frac{\boldsymbol{(x'x)^{-1} x'y}}{\sqrt{\sigma^2 \boldsymbol{(x'x)^{-1}}}}$. This is easily shown to be equivalent to

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

If σ^2 is unknown, we estimate it by $\hat{\sigma}^2 = \frac{\sum_{i=1}^{N} (AR_i - \hat{\beta}_{OLS})^2}{N - 1}$. Then σ is replaced with $\hat{\sigma}$, in the Z formula, and critical *t*-values are used for hypothesis testing.

The preceding analysis considers the case when there is only one day in the testing window. But suppose there are multiple periods for the testing period, $t=T_1, T_1+1, ..., T_2$. The extension is straightforward. Redefine the above such that

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

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

Once again, the OLS estimate of β, $\hat{\beta}_{OLS}$, is efficient. $\hat{\beta}_{OLS} = \boldsymbol{(x'x)^{-1} x'y}$. In this case,

$$\hat{\beta}_{OLS} = \frac{\sum_{i=1}^{N}\sum_{t=T_1}^{T_2} AR_{it}}{N(T_2 - T_1 + 1)} = ACAR,$$

where ACAR is the “average cumulative abnormal return”.

If σ^2 is known, then $Var(\hat{\beta}_{OLS}) = \sigma^2 \boldsymbol{(x'x)^{-1}}$, and $s.e.(\hat{\beta}_{OLS}) = \sqrt{\sigma^2 \boldsymbol{(x'x)^{-1}}}$, which is easily shown to be equivalent to $s.e.(\hat{\beta}_{OLS}) = \dfrac{\sigma}{\sqrt{N(T_2 - T_1 + 1)}}$. If σ^2 is unknown, we estimate it by $\hat{\sigma}^2 = \dfrac{\sum_{i=1}^{N}\sum_{t=T_1}^{T_2}(AR_{it} - \hat{\beta}_{OLS})^2}{(N(T_2 - T_1 + 1)) - 1}$.

5.2.2. The Generalized Case: Multiple-markets, Single-listing (Errors are heteroscedastic but cross-sectionally independent)

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

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

where $\boldsymbol{y}$ is an $N \times 1$ vector of abnormal returns; $\boldsymbol{x}$ is an $N \times 1$ vector of ones, and β is a scalar that equals the mean of the distribution of abnormal returns across multiple markets. Under the assumption that errors are heteroscedastic but cross-sectionally independent,

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

In this case, the OLS estimate of β is inefficient. The source of this inefficiency lies in the fact that OLS gives equal weight to every observation. The solution to this problem is to assign different weights to the individual observations. The estimation procedure that assigns an “efficient” set of weights is called Generalized Least Squares (GLS). Define a “weighting matrix” $\boldsymbol{P}$, where $\boldsymbol{P}$ is an $N \times N$, symmetric, invertible matrix such that $\boldsymbol{P'P} = \boldsymbol{\Omega}^{-1}$. Given $\boldsymbol{\Omega}$ above, it is easily confirmed that

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

Assuming the σ_i^2, $i=1,2,\ldots,N$ are known, the GLS estimator of β is given by $\hat{\beta}_{GLS} = (\boldsymbol{x'\Omega^{-1}x})^{-1}\boldsymbol{x'\Omega^{-1}y}$, $Var\left(\hat{\beta}_{GLS}\right) = (\boldsymbol{x'\Omega^{-1}x})^{-1}$, and $s.e.\left(\hat{\beta}_{GLS}\right) = \sqrt{(\boldsymbol{x'\Omega^{-1}x})^{-1}}$. Alternatively, define $\tilde{\boldsymbol{x}} = \boldsymbol{Px}$ and $\tilde{\boldsymbol{y}} = \boldsymbol{Py}$. Then $\hat{\beta}_{GLS} = (\tilde{\boldsymbol{x}}'\tilde{\boldsymbol{x}})^{-1}\tilde{\boldsymbol{x}}'\tilde{\boldsymbol{y}}$, $Var\left(\hat{\beta}_{GLS}\right) = (\tilde{\boldsymbol{x}}'\tilde{\boldsymbol{x}})^{-1}$, and $s.e.\left(\hat{\beta}_{GLS}\right) = \sqrt{(\tilde{\boldsymbol{x}}'\tilde{\boldsymbol{x}})^{-1}}$. In other words, $\hat{\beta}_{GLS}$ is identical to OLS applied to this equation:

$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{x}}\beta + \tilde{\boldsymbol{\varepsilon}}$, where $\tilde{\boldsymbol{x}} = \boldsymbol{Px}$, $\tilde{\boldsymbol{y}} = \boldsymbol{Py}$, and $\tilde{\boldsymbol{\varepsilon}} = \boldsymbol{P\varepsilon}$. Note that $\tilde{\boldsymbol{\varepsilon}} \sim N\left(\boldsymbol{0_N}, \boldsymbol{P\Omega P'}\right) = N\left(\boldsymbol{0_N}, \boldsymbol{I_N}\right)$.

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

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

Interestingly, $Z_t = \frac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \frac{\boldsymbol{(\tilde{x}'\tilde{x})^{-1}\,\tilde{x}'\tilde{y}}}{\sqrt{\boldsymbol{(\tilde{x}'\tilde{x})^{-1}}}}$ is <u>*NOT*</u> equal to $Z_{ASAR_t} = \frac{\sum_{i=1}^{N}\left({AR_{it}}/{\sigma_i} \right)}{\sqrt{N}}$. We can see this by noting that:

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

Z_{ASAR_t}, and its multiple period analog, $Z_{ASCAR_{T1,T2}}$ are commonly used for hypothesis testing of abnormal returns in the presence of heteroscedastic returns (Aybar & Ficici, 2009; Doukas & Travlos, 1988; Mikkelson & Partch, 1986; Patell, 1976).

5.2.3. What Hypothesis Corresponds to Z_{ASAR} and Z_{ASCAR}?

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

Consider the following regression:

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

where

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

Assuming the $\sigma_i^{\,2}$, $i=1,2,...,N$ are known, the OLS estimator of γ is $\hat{\gamma}_{OLS} = \boldsymbol{(x'x)^{-1} x'\tilde{y}}$, which is easily shown to be equivalent to $ASAR_t = \frac{\sum_{i=1}^{N} \left({AR_{it}}/{\sigma_i} \right)}{N}$. The OLS estimate of γ is efficient. Further, $Var(\hat{\gamma}_{OLS}) = \boldsymbol{(x'x)^{-1}}$, and $s.e.(\hat{\beta}_{OLS}) = \sqrt{\boldsymbol{(x'x)^{-1}}}$, which is easily shown to be equivalent to $s.e.(\hat{\gamma}_{OLS}) = \frac{1}{\sqrt{N}}$. To test the null hypothesis that $\gamma = 0$, form the Z statistic, $Z = \frac{\hat{\gamma}_{OLS}}{s.e.(\hat{\gamma}_{OLS})} = \frac{\boldsymbol{(x'x)^{-1} x'\tilde{y}}}{\sqrt{\boldsymbol{(x'x)^{-1}}}}$. This is easily shown to be equivalent to

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

Thus, the Z statistic, $Z_{ASAR_t} = \frac{\sum_{i=1}^{N} \left({AR_{it}}/{\sigma_i} \right)}{\sqrt{N}} = \sqrt{N} \cdot ASAR_t$, corresponds to the null hypothesis, $H_0 : \gamma = 0$. This contrast with the Z statistic, corresponding to the GLS estimate of β , $H_0 : \beta = 0$. Note that γ and β are different. β is the mean of the distribution of abnormal returns, AR_{it}. γ is the mean of the distribution of <u>standardized</u> abnormal returns, $\frac{AR_{it}}{\sigma_i}$.

5.2.4. The Generalized Case Two: Multiple-markets and Multi-listings (Errors are heteroscedastic and cross-sectionally dependent)

We move to multiple-markets and the multi-listing case, where the error structure is characterized by heteroscedasticity and cross-sectional dependence. The more integrated the markets, the more serious the cross-sectional correlation between pair returns. OLS is inefficient because it ignores these dependences and weights them as if they were completely independent observations. This gives too much weight to correlated observations. GLS solves this problem by "efficiently" weighting the observations via the error variance-covariance matrix, $\boldsymbol{\Omega}$.

We start off by considering a daily testing period (corresponding to daily abnormal returns), but then expand to allow for a multiple-day testing period (corresponding to cumulative abnormal returns). Define AR_{ijt} as the abnormal returns from security *i* listed in market *j* at time *t*. Note that this allows the same security to be listed in more than one market at the same time.

Let there be a total of $\tilde{N}$ observations of AR_{ijt} for given *t*. We represent the associated DGP of abnormal returns, AR_{ijt}, be given by

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

where $\boldsymbol{y}_t$ is an $N \times 1$ vector of abnormal returns; $\boldsymbol{x}_t$ is an $N \times 1$ vector of ones, and β is a scalar that equals the mean of the distribution of abnormal returns across multiple markets. $\boldsymbol{\varepsilon}_t$ is an $\tilde{N}?$ vector of error terms, $\boldsymbol{\varepsilon}_t \sim N\left(\boldsymbol{0}_{\tilde{N}}, \boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{\tilde{N}}^2 \end{bmatrix}\right)$, where a $\boldsymbol{0}_{\tilde{N}}$ is an $\tilde{N} \times 1$ vector of zeroes and $\boldsymbol{\Omega}$ is an $\tilde{N} \times \tilde{N}$ matrix, where the variances of the $\tilde{N}$ abnormal returns are given on the main diagonal.

We can better visualize the problem with an example. Let

(7) $$\boldsymbol{y_t} = \begin{pmatrix} AR_{11t} \\ AR_{12t} \\ AR_{13t} \\ AR_{21t} \\ AR_{23t} \\ AR_{32t} \\ AR_{43t} \end{pmatrix}$$

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

Define $\boldsymbol{P}$ such that $\boldsymbol{P'P = \Omega^{-1}}$. Pre-multiplying (6) by $\boldsymbol{P}$ gives

(8) $$\boldsymbol{Py_t = Px_t\beta + P\varepsilon_t}$$

Let us rewrite (8) as

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

where $\tilde{\mathbf{y}}_t$ is an $\tilde{N} \times 1$ vector of <u>standardized </u>abnormal returns, $\tilde{\boldsymbol{y}}_t = \boldsymbol{Py}_t$,

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

$\tilde{\boldsymbol{x}}_t = \boldsymbol{Px}_t$ and $\tilde{\boldsymbol{\varepsilon}}_t = \boldsymbol{P\varepsilon}_t$.

We now allow for correlated abnormal returns when the same security is listed in more than one market. Let $\tilde{\varepsilon}_t \sim N(\boldsymbol{0}_{\tilde{N}}, \tilde{\boldsymbol{\Omega}})$, where $\tilde{\boldsymbol{\Omega}}$ is the $\tilde{N} \times \tilde{N}$ variance-covariance matrix corresponding to the standard abnormal returns $\tilde{y}_t$.

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

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

Similar to before, define $\tilde{\boldsymbol{P}}$ (where $\tilde{\boldsymbol{P}}$ is $\tilde{N} \times \tilde{N}$) such that $\tilde{\boldsymbol{P}}'\tilde{\boldsymbol{P}} = \tilde{\boldsymbol{\Omega}}^{-1}$. Assuming the σ_{ijt} and $\rho_{ij,ik}$ $i=1,2,\ldots,N$ are known, the GLS estimator of β is

$$(12) \qquad \hat{\beta}_{GLS} = (\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\mathbf{x}})^{-1}\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}},$$

$Var\left(\hat{\beta}_{GLS}\right) = (\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\mathbf{x}})^{-1}$, and $s.e.\left(\hat{\beta}_{GLS}\right) = \sqrt{(\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\mathbf{x}})^{-1}}$. To test the null hypothesis that $\beta = 0$, we form the Z statistic,

$$(13) \qquad Z_t = \frac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \frac{(\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\mathbf{x}})^{-1}\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}}{\sqrt{(\tilde{\mathbf{x}}'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\mathbf{x}})^{-1}}}.$$

Given $\tilde{\boldsymbol{\Omega}}, \tilde{\boldsymbol{P}}$ is easily calculated using a Cholesky decomposition. The only remaining twist is the determination of $\tilde{\boldsymbol{\Omega}}$, which involves estimating the individual elements $\rho_{ij,ik}$. To achieve this, we follow a three-step process based on the studentized residual, which is the in-sample, standardized residual from estimations of the market model.

First, for each *i* and *j*, we estimate the market model during the estimation period, $s = 1, 2, \ldots, s$:

(14) $R_{ijs} = \alpha_{ij} + \beta_{ij} Rm_{js} + \varepsilon_{ijs}$.

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

We collect the explanatory variables in the matrix, $\boldsymbol{X_{ij}}$:

$$\boldsymbol{X_{ij}} = \begin{pmatrix} 1 & Rm_{j1} \\ 1 & Rm_{j2} \\ \vdots & \vdots \\ 1 & Rm_{jT'} \end{pmatrix}$$

Define the "hat" matrix

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

The standard deviation of the *s*th residual associated with estimation of equation (14) can be estimated by

(15) $\sigma_{ijs} = \hat{\sigma}_{ij}\sqrt{1 - h^{s}_{ij}}$

where h^{s}_{ij} is the *s*th diagonal element of $\boldsymbol{H_{ij}}$ and $\hat{\sigma}_{ij}$ is the standard error of the estimate from equation (14). Thus, for each *j* and *k*, the sample correlation of $\dfrac{AR_{ijs}}{\hat{\sigma}_{ij}\sqrt{1-h^{s}_{ij}}}$ and $\dfrac{AR_{iks}}{\hat{\sigma}_{ik}\sqrt{1-h^{s}_{ik}}}$ can be used to estimate $\rho_{ij,ik}$.

In the generalized multiple markets and multi-listing case with daily returns, the GLS estimator $\hat{\beta}_{GLS}$ (see equation 12) is used to estimate β in equation (6). Hypothesis testing proceeds by comparing Z_t (see equation 13) with the appropriate critical *t* value.

Now suppose there are multiple periods for the testing period, $t=T_1, T_1+1, \ldots, T_2$.

Define $\tilde{\boldsymbol{Y}} = \begin{bmatrix} \tilde{\boldsymbol{y}}_{T_1} \\ \tilde{\boldsymbol{y}}_{T_1+1} \\ \vdots \\ \tilde{\boldsymbol{y}}_{T_2} \end{bmatrix}$, $\tilde{\boldsymbol{X}} = \begin{bmatrix} \tilde{\boldsymbol{x}}_{T_1} \\ \tilde{\boldsymbol{x}}_{T_1+1} \\ \vdots \\ \tilde{\boldsymbol{x}}_{T_2} \end{bmatrix}$, $\boldsymbol{\Sigma} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}} & \boldsymbol{0}_{\tilde{N}\tilde{N}} & \cdots & \boldsymbol{0}_{\tilde{N}\tilde{N}} \\ \boldsymbol{0}_{\tilde{N}\tilde{N}} & \tilde{\boldsymbol{\Omega}} & \cdots & \boldsymbol{0}_{\tilde{N}\tilde{N}} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0}_{\tilde{N}\tilde{N}} & \boldsymbol{0}_{\tilde{N}\tilde{N}} & \cdots & \tilde{\boldsymbol{\Omega}} \end{bmatrix}$, where $\tilde{\boldsymbol{Y}}$ and $\tilde{\boldsymbol{X}}$ are each $\tilde{N}(T_2 - T_1 + 1) \times 1$, $\boldsymbol{0}_{\tilde{N}\tilde{N}}$ is a zero matrix of size $\tilde{N} \times \tilde{N}$, and $\boldsymbol{\Sigma}$ is $\tilde{N}(T_2 - T_1 + 1) \times \tilde{N}(T_2 - T_1 + 1)$.

Then the corresponding GLS estimator of β in equation (6) is

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

$Var\left(\hat{\beta}_{GLS}\right) = (\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}})^{-1}$, and $s.e.\left(\hat{\beta}_{GLS}\right) = \sqrt{(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}})^{-1}}$. To test the null hypothesis that $\beta = 0$, form the Z statistic, $Z_{T1,T2} = \dfrac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \dfrac{(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}})^{-1}\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{Y}}}{\sqrt{(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}})^{-1}}}$.

Note that we can simplify the notation considerably. First note that

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

Thus,

$$\hat{\beta}_{GLS} = (\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{X}})^{-1}\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{\Sigma}}^{-1}\tilde{\boldsymbol{Y}} = (\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_t)^{-1}(\sum_{t=T_1}^{T_2}\tilde{\boldsymbol{x}}_t'\tilde{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{y}}_t);$$

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

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

This leads to the following statistic for multi-period testing of abnormal returns,

$$(16) \qquad Z_{T1,T2} = \frac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \frac{(\sum_{t=T_1}^{T_2} \tilde{x}_t' \tilde{\Omega}^{-1} \tilde{x}_t)^{-1} (\sum_{t=T_1}^{T_2} \tilde{x}' \tilde{\Omega}^{-1} \tilde{y}_t)}{\sqrt{(\sum_{t=T_1}^{T_2} \tilde{x}_t' \tilde{\Omega}^{-1} \tilde{x}_t)^{-1}}} = \sqrt{(\sum_{t=T_1}^{T_2} \tilde{x}_t' \tilde{\Omega}^{-1} \tilde{x}_t)^{-1}} (\sum_{t=T_1}^{T_2} \tilde{x}' \tilde{\Omega}^{-1} \tilde{y}_t) \ .$$

The intuition underlying the above procedure is straightforward. Suppose a researcher had, for a given event type, access to data from firms listed in multiple markets and multi-listings (where returns were both heteroscedastic and cross-sectionally correlated). The generalized approach outlined above adjusts their weights by the error variance covariance matrix, thus achieving an efficient weighting of individual observations. Note that $\hat{\beta}_{GLS}$, and the corresponding Z_t and $Z_{T1,T2}$ statistics, are designed to estimate and test hypotheses about β, the mean of the population of abnormal returns; and not γ, the mean of the population of standardized abnormal returns, such as reported by Aybar & Ficici (2009), Doukas & Travlos (1988) and Mikkelson & Partch (1986).

5.3. Application: Overseas Mergers and Acquisitions by Chinese Firms

In this section, we apply the approach described above to a sample of overseas mergers and acquisitions (OMAs) by non-financial Chinese firms between 1 January 1994 and 31 December 2009.[79] There are two reasons why this should be a useful setting for assessing the potential contribution of our generalized methodology. First, the geographical dispersion of OMAs means that information relevant to a particular event is also likely to be dispersed. For example, while mainland investors might be expected to have informational advantages concerning Chinese acquiring firms, foreign investors may be better informed about the overseas targets. Estimation of the total wealth effects emanating from OMAs requires aggregation of these individual-country information sets. Second, such aggregation

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

is unlikely to be revealed by the price reaction in a single market. Prior literature (Chen et al., 2010; Gagnon & Karolyi, 2004) suggests that the Chinese mainland markets are not well integrated with other markets and that deviations from price parity are both common and substantial.

5.3.1. Summary Information on Multi-listings

To be included in the sample, the acquiring Chinese firm must have its shares listed in at least one of the following exchanges: Shanghai and Shenzhen exchanges (China mainland), SEHK (Hong Kong, China), NYSE, AMEX or NASDAQ (US); have stock price information available from DataStream; and provide at least 137 days of continuous return data before and 10 days return after announcement date, of which fewer than 50% are zero return days. 157 OMA events initiated by a total of 96 Chinese acquirers satisfied these criteria.

Over a third of these deals involved target firms located in Hong Kong, with the remainder spread widely across six continents. With Hong Kong excluded, the US is the most frequent location of target firms.[80]

For our purposes, the most interesting aspect of this sample is the listing status, as summarized in Table 5.1, of the Chinese acquiring firms involved in the 157 OMA events. Of these, 111 events involve firms listed in a single market only – 50 in China, 30 in Hong Kong, China and 31 in US – while the remaining 46 are dual-listed (36) or triple-listed (10). In total, therefore, there are 213 return reactions in the sample once these multi-listings are taken into account. This compares with the 64 (157) observations available if only home (liquid) listings are used. However, this extended sample cannot simply be thought of as providing independent draws from a distribution – 102 of the 213 observations are related, in that they consist of double- or triple-listed shares of the same firm.

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

5.3.2. Summary Information on the Abnormal Return Correlations

Table 5.2 reports summary correlations between pair-listings. The abnormal return correlation drops with the decline of market integration.[81] We employ "lumped" instead of "trade to trade" returns to calculate daily return correlations because of different holiday distribution among nations or areas.

Chinese mainland exchanges are believed to be partly segmented with the rest of the world. A security multi-listed in the mainland and overseas is not exchangeable. Chinese mainland citizens are not allowed legally to invest in HK or the US. Price of H shares are well-known to be discounted relative to A shares.[82] The 20 Chinese mainland & US listing pairs, therefore, achieve a relatively low, average correlation of 0.1133. Although the Chinese mainland and Hong Kong markets are located in the same time zone, share the same language and similar culture, the 32 dual-listing pairs still demonstrate a low, average correlation of 0.0858. On the other hand, the Hong Kong market is generally regarded as being highly integrated with US markets. H share ADRs in US and Pilot program securities in HK are exchangeable. There is no citizenship restriction for mutual investment. Therefore, Hong Kong & US dual-listing pairs achieve high correlation of 0.6088 (note time zone differences keep the correlation from being higher).

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[81] Empirical studies show that correlation between different markets are pretty low: 0.0071-0.1232 for market return pairs (Yun et al., 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 (Eun & Shim, 1989; Hamao, Masulis, & Ng, 1990; Yun et al., 2005).

[82] 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.

We find evidence of price convergence in Hong Kong and US dual-listing pairs. The mean, absolute percentage difference of Hong Kong-US dual-listing pairs was only 4.8% in 2008 compared to 47.32% and 40.89% for the mainland-Hong Kong, mainland-US dual-listings, respectively (see Table 5.3).[83] Absolute percentage deviations for individual dual-listed shares are reported in Table 5.3 for reference.

5.3.3. The Comparison of OLS and GLS Estimators with Different Sample Sizes

Table 5.4 reports daily results for the OLS and GLS estimators using the three data sets: (i) Mainland-listing, (ii) Liquid-listing, and, (iii) Multi-listing. We first look at the OLS and GLS-1 results from the sample of 64 mainland-listings. The results from the two procedures are very similar. The estimates of the daily mean values of AR_{it} are approximately the same. Further, both procedures find statistical significance for day (-1) and day (2).

We next look at the sample of 157 liquid-listings. These include Chinese acquirers who list in all three markets: (i) Mainland, (ii) Hong Kong, and (iii) the U.S. The two procedures produce very different results for this sample. The major difference is that OLS finds significant day effects on day (-5), day (2), and day (3). The GLS-1 procedure finds no significant abnormal returns for any of the 21 days of the test period.

For the sample of 213 multi-listings, the three procedures get diverse results too. We find significant abnormal returns on day (-5), day (0), day (1), day (2) and day (3) for the OLS procedure. However, only the day (1) returns are significant at the 5% level for GLS-1; and only the day(-1) returns are significant for the GLS-2 procedure.

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

Table 5.5 reports the interval performance of Chinese OMAs. Once again, the results depend on the sample and the estimation periods. Interestingly, when it comes to statistical significance, the three procedures produce identical results within each sample, but results differ across samples. For the Mainland-listing sample, abnormal returns are significant on the (-5,-1) interval. In contrast, for the liquid-listing and Multi-listing samples, abnormal returns are significant on the (-1,1) interval. Across all three samples, the GLS-1 and GLS-2 results estimate CARs that are close to each other. The OLS results tend to be substantially larger.

Interval performance is generally considered to be more reliable than daily results, because aggregation tends to cancel out spurious findings. This is likely to be all the more true in the cross-listing case, when time zones and holidays affect the actual announcement dates and their stock price responses. Similar to aggregation across days is aggregation across markets. Including overseas markets allows “votes” of foreign investors to be counted.

So far, we report estimations of daily and interval performance on Chinese OMAs, for three different procedures and three different samples. But which set of estimates should we believe?

First, more observations are better. More observations provide more information. Compared to the 64 mainland-listings, the 157 liquid-listings include Chinese acquirers who list on overseas markets (HK-listings and US-listings). This rarely happens for acquirers from developed nations or areas. However, for firms from emerging markets, foreign-listing is a signal of international operations experience, and offers greater transparency and better investor protection. In other words, Chinese foreign-listed acquirers are more likely to be recognized as firms with better performance. The OMA performance estimation will be biased if foreign-listing acquirers are not embodied in the sample.

Similarly, market responses from multi-listings can not be simply replaced by single-listings. In our Chinese OMA case, many of the firms list on multiple markets. Multi-listings incorporate investors' responses of HK and US investors to Chinese OMA events in HK and US. Because of language, cultural linkages and different geographic distributions, mainland investors are more knowledgeable on acquirers whilst HK and U.S. investors may be better informed about foreign targets. These new information sources will be blocked if only single-listings are examined.

The results in Table 5.4 provide evidence that foreign- and multi-listings add new information in Chinese OMA performance. The three sample groups report diverse abnormal returns and Z-values. Take the GLS-1 procedure for example. The results for the 64 observations in the mainland-listings sample show significant positive abnormal returns on day (-1). In contrast, the GLS-1 procedure produces no significant abnormal returns for the 157 observations of the liquid-listing sample. This is evidence that foreign investors differ from Chinese investors in their evaluations of Chinese OMAs.

Having decided that the largest sample is best, the next question is which procedure produces the most reliable results. Our judgment is that the GLS-2 procedure is best because it weights observations on both heteroscedasticity and cross-sectional dependence. The use of multi-listed observations - which is desirable both because it increases sample size and allows a greater range of investor evaluations – argues for the GLS-2 procedures. The other two procedures treat multi-listed observations as though they are independent. Table 5.3 suggests that this assumption is not warranted.

In this respect the contrast between the GLS-1 and GLS-2 results is enlightening. The GLS-1 results suggest information delay whilst GLS-2 suggests information leakage. We are more likely to believe information leakage rather than information lag in OMA events. Mainland-listings report significant abnormal returns on day (-1). As home markets or liquid markets are regarded the key markets of information disclosure in finance literature, this is evidence of information leakage.[84] The information lag result may be due to U.S.-listings, which are subject to a 12 hour time zone delay. GLS-1 weights US-listings equally with mainland- or HK- listings, which "overweights" these observations if they are correlated with the other markets (especially HK).

In all, we argue that results from the multi-listing sample/GLS-2 procedure provide the most reliable appraisal of Chinese OMA performance. We conclude that markets respond positively to Chinese OMA events with an overall 0.22% cumulative abnormal returns on the interval (-1,1). Information leakage happens on day (-1) with a significant 0.29% abnormal return before the OMA announcement.

5.4. Conclusion

This chapter extends event-study analysis to cases where firms list their stocks in multiple exchanges and with multi-listings. These additional listings offer extra information about investors that are not included in single, home market settings; and provide an opportunity to substantially increase sample size. We develop a generalized event-study methodology that explicitly incorporates the relationship of share price performance across multiple exchanges.

The generalized methodology is likely to be important for performance evaluation in emerging markets, where home markets are partly segmented and with less investor protection, and where data for listed securities are relatively few. Using the information from multi-listings allows one to maximize the information available from a relatively small sample of firms. Our generalized approach incorporates heterocsedasticity and cross-sectional correlation in abnormal returns, and provides an efficient weighting of observations.

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[84] Although foreign listing occupies 70% of the total sample (64 mainland listings, 76 Hong Kong listings and 73 US listings), Chinese mainland listings achieve the most liquid ones among multi-listings in our sample according to trading volume and market depth criteria.

We compare our approach with the standardized event study approach used in Aybar & Ficici (2009), Doukas & Travlos (1988) and Mikkelson & Partch (1986). We note that the standardized event study approach estimates the mean of the distribution of <u>standardized</u> abnormal returns. In contrast, there is generally more interest in the mean of the distribution of (non-standardized) abnormal returns. Our generalized event study approach estimates the latter. Further, it produces consistent and asymptotically efficient estimates.

We apply this new event study approach to estimate wealth effects of Chinese OMA acquirers. We include cross-listings in China mainland, Hong Kong and US markets, where markets are segmented or partially segmented. We compare outcomes from three methodologies (OLS, GLS-heterosedasticity and GLS-heteroscedasticity/cross-sectional correlation) and three sample sizes (64 mainland-listings, 157 single-listings in multiple markets and 213 multi-listings in multiple markets). The inclusion of multi-listed observations provides a more robust evaluation of OMA events. Our generalized methodology allows one to use these additional observations while providing consistent and asymptotically efficient estimates of mean abnormal returns.

Chapter Six Concluding Remarks

Chinese overseas merger and acquisition (OMA) activity is growing very fast. The starting point for this thesis is an investigation of their stock market performance and corresponding determinants using event study methodology. China is well known as a "market economy model dominated by political capital". Political connections are considered to be supportive resources for Chinese OMA activities. Accordingly, we examine the Chinese Go Global policy and its impact on OMA performance. Moreover, we look at whether government strategy of industry restructuring has positional advantages on OMA performance in the long-run.

We employ event study methodology to investigate stock market performance of Chinese OMAs. The market model and the Fama and French Three-Factor Model are employed as benchmark models to evaluate abnormal returns in the short-and long-run respectively.

M&A performance determinants are far more complicated in international settings. In this thesis, we test their effects on OMA performance by grouping them into bidder's endowment, transaction details and target location variables. To be fully informed by more transparent and investor protection markets, we include multi-listing stocks of Chinese acquirers in three overseas markets (the Chinese mainland market, the Hong Kong market and the U.S. market). We find markets respond disparately on Chinese OMAs. Further, OLS tends to overestimate the wealth effect of Chinese OMAs when cross-listings are included in the sample. We then develop GLS procedures to "weight" multi-listing observation according to the independent information they provide.

We find that markets respond positively to OMA announcement by Chinese acquirers. However, the short-run effect is small: the average daily rate of return over the (-1,1) window is 0.22%. The performance remains positive one and two years after OMAs, though not significant. It shrinks three years after OMAs, but remains non-negative. Using a Blinder-Oaxaca Decomposition procedure, we find that markets responded less favourably to OMA announcements after the Chinese Go Global policy, though the difference is not significant. There is no evidence that Go Global destroyed shareholder's value in the short-run. Nor that top managers were led into unprofitable decision-making because of the promotive policy of government.

Performance determinants differ in explaining short- and long-run Chinese OMA performance. The multivariate regressions indicate mixed results for industry restructuring purpose of Chinese OMAs. Significantly negative OMA performance is found in the natural resources/high-technology sector in the short-run. In contrast, we find that in the long-run performance for this sector is positive. Government ownership is significantly negatively related to three-year long-run performance. No other variables are consistently related to Chinese OMAs performance.

This thesis is one of the few studies on Chinese short- and long-run OMA performance. Furthermore, this thesis is the first to incorporate multi-listing stock performance in an event study. We argue that Chinese multi-listings contribute additional information about OMA events. Therefore, we develop a new approach to avoid clustering and overestimation issues in multi-listings and achieve consistent performance results. We find the actual abnormal returns of Chinese OMAs are much smaller (CAR [-1,1] decreases from 1.2% to 0.22%) after Hong Kong and U.S. multi-listings are included in the estimation. We believe this approach can be applied to empirical studies in emerging market settings, where markets are segmented with the world and weak investor protections exist in domestic markets.

The findings of this study can be a reference for top managers of Chinese acquirers and foreign incumbents. Although there are diverse motives for cross-border OMAs, it is extremely important for top managers to be better informed about their performance. The hubris and herding behaviours are more likely to happen when Chinese top managers are not well informed, or lack world-class M&A capacity under the Go Global policy environment.

Further, Chinese OMAs represent a potential threat- but also an opportunity - for western incumbents. A better understanding of their situation helps host countries and targets to figure out ways to profit from OMA deals and make them win-win for all parties.

The results can also be a reference to individual investors. As we include three share markets' responses (the Chinese mainland markets, the Hong Kong markets and the US markets) in this research, it provides comprehensive information about Chinese OMA events. The results about short-run performance and its determinants provide possible arbitrage opportunities for investors. Results about long-run performance and its determinants can assist investors to develop a sustainable investment strategy.

Last but not the least, our findings can be a reference for policy makers. Chinese governments see overseas M&As as a means to lock-in strategy resources and drive industry restructuring. The long-run goal is to help Chinese MNEs to achieve positions of competitive global power, allowing them to keep more of the rewards from international trade. Empirical studies of OMA performance can help us understand whether such policies have been successful, at least for emerging economies.

Tables

Table 3.1 Distribution of Deals Over Time

	Deal number	Deal value available	Deal value ($ mil)	Average value ($ mil)
1994	1	1	98.5	98.5
1995	1	1	1.3	1.3
1996	2	2	482.1	241
1997	4	3	360.6	120.2
1998	7	6	262.5	43.7
1999	4	3	45.9	15.3
2000	6	4	75.5	18.9
2001	6	4	50.5	12.6
2002	11	10	2098.9	209.9
2003	9	7	2048.6	292.7
2004	16	9	2367.49	263.05
2005	8	6	4243.59	707.27
2006	12	9	10282.16	1142.46
2007	21	15	2437.80	162.52
2008	20	12	2346.35	195.53
2009	29	21	5794.60	275.93
Total	157	113	32996.3	292.00

Source: SDC Platinum M&A database

Table 3.2 Target Location

Nation or Area	Number of deals	Deal value available	Total value of deals ($mil)	Average value of deals ($mil)
Developed nations or Area				
Hong Kong[1]	58	45	5174.62	114.99
United States	17	10	2476.79	247.68
Australia	12	10	3690.42	369.04
Canada	6	6	2553.19	425.53
Japan	4	3	169.91	56.64
United Kingdom[2]	4	3	6886.50	2295.50
Germany	3	0	0	0
Italy	3	1	0.13	0.13
Netherlands	2	1	148.50	148.50
France	1	1	8.66	8.66
New Zealand	1	1	26.18	26.18
Sum	111	81	21134.89	260.9245
Asia				
Singapore	6	4	1879.88	469.97
Indonesia	5	4	1129.49	282.37
South Korea	3	3	473.64	157.88
Azerbaijan	2	2	70	35
India	2	2	9.49	4.75
Kazakhstan	2	1	200.00	200.00
Pakistan	2	2	744	372
Russian Fed	2	2	3600	1800
Taiwan	2	1	2.17	2.17
Malaysia	1	1	11.47	11.47
Mongolia	1	0	0	0
Philippines	1	1	70	70
Thailand	1	1	0.58	0.58
Vietnam	1	0	0	0
Sum	31	24	8190.72	341.28
Africa				
Nigeria	2	1	2692	2692
Zambia	2	0	0	0
Chad	1	1	202.5	202.5
Tunisia	1	0	0	0
Sum	6	2	2894.5	1447.25

Nation or Area	Number of deals	Deal value available	Total value of deals ($mil)	Average value of deals ($mil)
South America				
British Virgin	3	2	33.21	16.605
Brazil	2	2	520	260
Peru	2	1	200	200
Cayman Islands	1	1	23	23
Mexico	1	0	0	0
Sum	9	6	776.21	129.3683
Total	157	113	32996.3	292.00

[1] We include Hong Kong targets in the overseas M&A group because most researchers argue that Hong Kong has obviously different economic system away from Chinese mainland.

[2] Both of the target firms are PetroKazakhstan and with the nationality of United Kingdom in SDC database because they argue that the headquarter of PetroKazakhstan is in the United Kingdom. However, most Chinese consider it as a Canadian firm. In Zephyr M&A database, the nationality of PetroKazakhstan is Canada too.

Table 3.3 Industry Distribution

Target industry sector	Number of deals	Deal value available	Deal value $ million	Average value $ million	Deal number before 2002[3]	Average Value Before 2002 $ million	Deal number after 2002	Average Value after 2002 $ million
Telecommunication and electronics, Prepacked software[4]	45	32	4993	156	11 (35.5%)	16	34 (27%)	195.2
Energy and natural resources[5]	42	29	18557.5	639.9	1 (3.2%)	0	41 (32.5%)	639.9
Miscellaneous business services[6]	14	9	503	55.9	2 (6.5%)	9.2	12 (9.5%)	69.2
Miscellaneous manufacturing Products[7]	20	8	284.7	35.6	5 (16.1%)	10.3	15 (11.9%)	60.9
Electric, gas and water distribution, construction	9	5	469.4	93.9	4 (12.9%)	13.3	5 (4%)	214.8
Wholesales, retail, trade[8]	11	7	466.6	66.7	4 (12.9%)	81.6	7 (5.6%)	46.8
Transportation[9]	11	11	2459.3	223.6	3 (9.7%)	279.2	8 (6.3%)	202.7
Chemicals and Drugs[10]	5	3	93.3	31.1	1 (3.2%)	1.3	4 (3.2%)	46
Total	157	104	27826.8	267.6	31	57.4	126	330.6

[3] The percentage in the brackets shows the proportion in total deals in the period.
[4] "Telecommunication and Electronics, Prepackaged Software Industry" consists of the following SDC categories: "Computer and Office Equipment;" "Telecommunications;" "Electronic and Electrical Equipment;" "Communications Equipment;" and "Prepackaged Software."

[5] "Energy and Natural Resources" consists of the following SDC categories: "Oil and Gas;" "Petroleum Refining;" "Mining;" "Metal and Metal Products;" and "Agriculture, Forestry, and Fishing."
[6] "Wholesale, Retail, Trade" consists of the following SDC categories: "Wholesale Trade-Nondurable Goods;" "Wholesale Trade-Durable Goods;" and "Miscellaneous Retail Trade."
[7] "Miscellaneous Manufacturing Products" consists of the following SDC categories: "Measuring, Medical, Photo Eqipment;" "Clocks;" "Food and Kindred Products;" "Stone, Clay, Glass, and Concrete Products;" "Textile and Apparel Products;" "Wood Products, Furniture, and Fixtures;" "Machinery;" "Miscellaneous Manufacturing;" and "Transportation Equipment."
[8] "Transportation" consists of the following SDC categories: "Transportation and Shipping (except Air);" and "Air Transportation and Shipping."
[9] "Miscellaneous Business Services" consists of the following SDC categories: "Business Services;" "Health Services;" "Investment and Commodity Firms, Dealers, Exchanges;" and "Radio and Television Broadcasting Stations."
[10] "Chemicals and Drugs" consists of the following SDC categories: "Drugs;" and "Chemicals and Allied Products."

Table 3.4 Daily Performance

DAILY	AAR	ASAR[11]	Z_{Daily}	*p-value*
-10	0.0026	0.0980	1.2283	0.2193
-9	0.0025	0.1065	1.3340	0.1822
-8	-0.0003	-0.0059	-0.0736	0.9413
-7	-0.0031	-0.0734	-0.9198	0.3577
-6	-0.0017	-0.0742	-0.9303	0.3522
-5	0.0061	0.1323	1.6575	0.0974
-4	-0.0023	0.0184	0.2306	0.8176
-3	0.0000	0.0202	0.2529	0.8004
-2	-0.0022	-0.0576	-0.7222	0.4702
-1	0.0036	0.1513	1.8960	0.0580
0	0.0044	0.0835	1.0459	0.2956
1	0.0040	0.1203	1.5068	0.1319
2	-0.0059	-0.1404	-1.7598	0.0784
3	-0.0056	-0.1520	-1.9049	0.0568
4	-0.0024	-0.0950	-1.1909	0.2337
5	0.0014	0.0930	1.1655	0.2438
6	-0.0017	-0.0783	-0.9811	0.3265
7	0.0045	0.1019	1.2764	0.2018
8	0.0005	0.0539	0.6749	0.4997
9	-0.0006	-0.0645	-0.8087	0.4187
10	-0.0031	-0.0952	-1.1926	0.2330

Note: AAR, ASAR, and Z_{Daily} are defined in the text (Section 3.3.2.). Days are identified relative to the announcement day (Day 0). The sample consists of 157 observations.

[11] Please see Section 3.3.2. for details.

Table 3.5 Interval Performance

INTERVAL	ACAR	ASCAR	$Z_{Interval}$	*p-value*
(-10,-5)	0.0061	0.0748	0.9374	0.3486
(-10,-1)	0.0052	0.0998	1.2502	0.2112
(-5,-1)	0.0051	0.1183	1.4824	0.1382
(-1,1)	0.0120	0.2050	2.5684	0.0102
(1,5)	-0.0085	-0.0779	-0.9764	0.3288
(5,10)	0.0009	0.0044	0.0548	0.9563
(1,10)	-0.0090	-0.0811	-1.0165	0.3094
(-5,5)	0.0010	0.0524	0.6565	0.5115
(-10,10)	0.0006	0.0311	0.3894	0.6970
(-2,2)	0.0039	0.0702	0.8795	0.3791
(-3,3)	-0.0017	0.0095	0.1189	0.9054

Note: ACAR, ASCAR, and $Z_{Interval}$ are defined in the text (Section 3.3.2.). Days are identified relative to the announcement day (Day 0). The sample consists of 157 observations.

Table 3.6 Three Markets, Daily Performance

	MAINLAND				HK				US			
DAILY	**AAR**	**ASAR**	**Z_{Daily}**	***p-value***	**AAR**	**ASAR**	**Z_{Daily}**	***p-value***	**AAR**	**ASAR**	**Z_{Daily}**	***p-value***
-10	0.0011	0.0499	0.3993	0.6897	0.0012	0.0956	0.8334	0.4046	0.0055	0.1241	1.0599	0.2892
-9	0.0037	0.1511	1.2087	0.2268	0.0032	0.1576	1.3742	0.1694	0.0008	0.0346	0.2954	0.7677
-8	0.0018	0.1018	0.8141	0.4156	-0.0036	-0.1885	-1.6432	0.1003	0.0010	0.0491	0.4193	0.6750
-7	0.0001	0.0043	0.0341	0.9728	0.0000	0.0101	0.0876	0.9302	-0.0096	-0.2721	-2.3252	0.0201
-6	0.0005	-0.0126	-0.1011	0.9194	-0.0028	-0.1710	-1.4906	0.1361	-0.0010	-0.0344	-0.2940	0.7687
-5	0.0040	0.1447	1.1576	0.2470	0.0037	0.0350	0.3049	0.7604	0.0074	0.1586	1.3554	0.1753
-4	0.0009	0.0936	0.7488	0.4540	0.0064	0.1924	1.6775	0.0934	-0.0116	-0.2533	-2.1640	0.0305
-3	-0.0003	-0.0159	-0.1269	0.8990	0.0008	0.0838	0.7308	0.4649	-0.0022	-0.0992	-0.8479	0.3965
-2	0.0016	0.0764	0.6115	0.5409	-0.0025	-0.0928	-0.8087	0.4187	-0.0069	-0.1988	-1.6989	0.0893
-1	0.0087	0.3845	3.0763	0.0021	0.0015	0.0564	0.4914	0.6231	0.0005	-0.0394	-0.3368	0.7363
0	0.0003	0.0654	0.5234	0.6007	0.0071	0.1847	1.6103	0.1073	0.0052	-0.0173	-0.1479	0.8824
1	-0.0010	-0.0797	-0.6379	0.5235	0.0032	0.1740	1.5168	0.1293	0.0133	0.4253	3.6342	0.0003
2	-0.0060	-0.3058	-2.4462	0.0144	-0.0009	0.0462	0.4029	0.6870	-0.0089	-0.1758	-1.5024	0.1330
3	0.0002	0.0118	0.0945	0.9247	-0.0093	-0.3142	-2.7388	0.0062	-0.0043	-0.0645	-0.5508	0.5817
4	-0.0045	-0.1977	-1.5812	0.1138	0.0016	0.0791	0.6899	0.4903	-0.0007	-0.0254	-0.2167	0.8284
5	0.0038	0.1593	1.2740	0.2027	0.0003	0.0389	0.3392	0.7344	0.0018	0.1274	1.0882	0.2765
6	-0.0010	-0.0044	-0.0353	0.9718	-0.0009	-0.0728	-0.6348	0.5256	0.0017	0.0340	0.2902	0.7716
7	0.0029	0.1451	1.1607	0.2458	0.0001	0.0201	0.1749	0.8612	0.0073	0.0527	0.4502	0.6525
8	0.0010	0.1051	0.8412	0.4002	0.0004	-0.0632	-0.5510	0.5816	0.0015	0.1365	1.1662	0.2436
9	-0.0023	-0.1657	-1.3253	0.1851	0.0035	0.1267	1.1044	0.2694	-0.0028	-0.1235	-1.0556	0.2911
10	-0.0034	-0.1807	-1.4460	0.1482	-0.0014	-0.0150	-0.1309	0.8958	-0.0036	-0.0756	-0.6463	0.5181
Obs.	64				76				73			

Note: AAR, ASAR, and Z_{Daily} are defined in the text (Section 3.3.2.). Days are identified relative to the announcement day (Day 0).

Table 3.7 Three Markets, Interval Performance

INTERVAL	Mainland ACAR	Mainland ASCAR	Mainland $Z_{Interval}$	Mainland *p-value*	HK ACAR	HK ASCAR	HK $Z_{Interval}$	HK *p-value*	US ACAR	US ASCAR	US $Z_{Interval}$	US *p-value*
(-10,-5)	0.0111	0.1793	1.4340	0.1516	0.0018	-0.0250	-0.2179	0.8275	0.0041	0.0244	0.2085	0.8348
(-10,-1)	0.0220	0.3092	2.4736	0.0134	0.0080	0.0565	0.4925	0.6224	-0.0161	-0.1679	-1.4347	0.1514
(-5,-1)	0.0149	0.3056	2.4450	0.0145	0.0099	0.1229	1.0715	0.2839	-0.0128	-0.1933	-1.6512	0.0987
(-1,1)	0.0081	0.2138	1.7100	0.0873	0.0117	0.2396	2.0891	0.0367	0.0190	0.2128	1.8184	0.0690
(1,5)	-0.0076	-0.1843	-1.4744	0.1404	-0.0051	0.0108	0.0939	0.9252	0.0012	0.1284	1.0968	0.2727
(5,10)	0.0010	0.0240	0.1916	0.8481	0.0019	0.0141	0.1232	0.9019	0.0059	0.0618	0.5278	0.5976
(1,10)	-0.0104	-0.1621	-1.2970	0.1946	-0.0035	0.0063	0.0546	0.9565	0.0053	0.0983	0.8403	0.4008
(-5,5)	0.0076	0.1015	0.8122	0.4167	0.0118	0.1458	1.2713	0.2036	-0.0064	-0.0490	-0.4184	0.6757
(-10,10)	0.0119	0.1158	0.9262	0.3544	0.0116	0.0836	0.7289	0.4661	-0.0056	-0.0518	-0.4425	0.6582
(-2,2)	0.0037	0.0630	0.5040	0.6142	0.0083	0.1648	1.4368	0.1508	0.0032	-0.0027	-0.0232	0.9815
(-3,3)	0.0036	0.0517	0.4137	0.6791	-0.0001	0.0522	0.4554	0.6489	-0.0033	-0.0642	-0.5483	0.5835
Observation	64				76				73			

Note: ACAR, ASCAR, and $Z_{Interval}$ are defined in the text (Section 3.3.2.). Days are identified relative to the announcement day (Day 0).

Table 3.8 Performance Before and After "Go Global"

	BEFORE POLICY: 1994-2001	AFTER POLICY: 2002-2009	POLICY IMPACT: DIFFERENCE
ACAR (-1,1)	0.0339	0.0066	-0.0273
ASCAR (-1,1)	0.5298	0.3120	-0.2178
$\mathbf{Z_{Interval}}$	1.7031	2.0222	-0.3529
p-value	0.0885	0.0432	0.7241
Observation	31	126	

Note: ACAR, ASCAR, and $Z_{Interval}$ are defined in the text (Section 3.3.2.). "Policy" is defined as the onset of the "Go Global" policy, defined as beginning on or near 2002.

Table 3.9 Variable Description

Dependent variable	CAR(-1,1), cumulative abnormal return
Independent variables	Description
Policy related variables	
POLICY	Dummy 1 if in and after year 2002, 0 if not
GOVTOWN	Dummy 1 if Government owned enterprises, 0 if not[12]
NATRES	Dummy 1 if natural resources industry targets, 0 if not
ITIN	Dummy 1 if technology-intensive targets, 0 if not
Control variables	
THK	Dummy 1 if HK target, 0 if not
INDREL	Dummy 1 if related (SIC 2-digit code), 0 if unrelated
ADVISOR	Dummy 1 if acquirer employed institutional advisor, 0 if not
FEX	US dollar depreciation according to Chinese RMB[13], daily data
CASH	Dummy 1 if cash payment, 0 if stock exchange
Alternative variables in robustness check	
CULDIS	Culture difference scores between China and the targets[14]
DEVDC	Dummy 1 if target is in developed country, 0 if not
TRAVALUE	Transaction value of the deal, in USD million
LNTRAVALUE	Log form of transaction value
MV6b	Market value 6 months before announcement
LNMV6b	Log form of market value 6 months before announcement
BM[15]	Book to market ratio
HKM	Dummy 1 if list in Hong Kong market, 0 if not
USM	Dummy 1 if list in US market, 0 if not
CRISIS	Dummy 1 if in and after year 2007, 0 if not

[12] Government owned enterprise is defined when the ultimate parent company is government owned in SDC Platinum.
[13] FEX is computed as following:

$$FEX = \frac{\frac{1}{n}\sum_{i=1}^{n} e_k - e_{ak}}{\frac{1}{n}\sum_{i=1}^{n} e_k}$$

e_k indicates the daily exchange rate of USD (units of dollars per unit of RMB) in the year 1994-2007;

e_{ak} indicates daily foreign exchange rate of the USD in the year of the announcement,

Positive FEX_k values indicate a cheaper dollar for the Chinese acquirers, while negative values indicate that the USD will be more expensive.

[14] Hofstede's Cultural dimensions scores are from http://www.geert-hofstede.com. The culture distance index equation from Kogut and Sing (1998) is:

$$CD_j = \sum_{i=1}^{4} \frac{\{(I_{ij} - I_{iN})^2 / V_i\}}{4}$$

Where CD_j indicates the culture distance index between country j and the home country;

I_{ij} indicates culture dimension score on ith item of country j;

I_{iN} indicates culture distance dimension score of home country while

V_i is the variance of culture distance dimension scores.

[15] When book-to-market ratio is calculated, we employ book value 1 year before the OMA and market value on announcement date.

Table 3.10 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variable					
CAR(-1,1)	157	0.0120	0.0716	-0.1380	0.6316
Policy related variables					
POLICY	157	0.8025	0.3994	0.0000	1.0000
GOVTOWN	157	0.4713	0.5008	0.0000	1.0000
NATRES	157	0.2675	0.4441	0.0000	1.0000
ITIN	157	0.3376	0.4744	0.0000	1.0000
Control variables					
THK	157	0.3694	0.4842	0.0000	1.0000
INDREL	157	0.5223	0.5011	0.0000	1.0000
ADVISOR	157	0.2994	0.4594	0.0000	1.0000
FEX	157	0.0931	0.6841	-0.0348	0.1515
CASH	157	0.5605	0.4979	0.0000	1.0000
Alternative variables for robustness checks					
CULDIS	144	1.4383	1.3883	0.1400	4.5890
DEVDC	157	0.7643	0.4258	0.0000	1.0000
TRAVALUE	113	292.0028	710.7058	0.1270	4141.179
LNTRAVALUE	113	3.6538	2.1808	-2.0636	8.3287
MV6b[16]	157	11433.36	36217.11	5.6700	330278
LNMV6b	157	7.3322	2.0992	1.7352	12.7077
BM[17]	136	0.6113	1.2526	0.0172	12.5893
HKM	157	0.3822	0.4875	0.0000	1.0000
USM	157	0.1975	0.3994	0.0000	1.0000
CRISIS	157	0.4459	0.4987	0.0000	1.0000

[16] MV6b means market value of securities 6 month before the announcement.
[17] When book-to-market ratio is calculated, I employ book value 1 year before the OMA and market value on announcement date.

Table 3.11 Correlation Coefficients

	Car(-1,1)	policy	govtown	natrel	itin	thk	indrel	advisor	Fex	cash	Culdis	devdc	lntrav~e	lnmv6b	y1bm	hkm	usm	crisis
Car(-1,1)	1																	
policy	-0.1522	1																
govtown	-0.0725	-0.0766	1															
natrel	0.0302	0.2636	0.3806	1														
itin	-0.1535	-0.0519	-0.2963	-0.4314	1													
thk	-0.0358	-0.3828	0.0175	-0.4328	0.2629	1												
indrel	-0.1536	0.2944	0.0089	0.0594	0.1704	-0.1134	1											
advisor	-0.0282	0.1495	0.1072	0.1077	-0.0255	-0.0105	0.0961	1										
fex	-0.0463	0.4503	-0.3081	0.0881	-0.069	-0.3594	-0.0157	0.0129	1									
cash	-0.054	0.1411	0.0134	0.1582	-0.1006	0.0396	0.0781	0.2426	0.0663	1								
culdis	0.0926	0.3009	-0.1186	0.2971	-0.1676	-0.7706	0.1032	0.0461	0.3583	-0.0409	1							
devdc	0.074	-0.1623	-0.2273	-0.3764	0.1108	0.425	-0.0503	0.1008	-0.0251	0.0223	0.1232	1						
lntravalue	-0.0902	0.2515	0.3804	0.2655	-0.0984	-0.1421	0.1567	0.5619	-0.0504	0.0567	0.1051	-0.0845	1					
lnmv6b	-0.1452	0.3546	0.4783	0.3277	-0.1394	-0.2334	0.2134	0.2074	0.105	0.1337	0.081	-0.2511	0.5711	1				
y1bm	-0.1405	-0.0877	0.0003	-0.1121	0.033	0.2023	-0.1595	-0.0752	0.032	-0.0864	-0.1728	0.0262	-0.0747	-0.3502	1			
hkm	-0.0095	-0.0709	0.4653	0.0873	-0.0902	0.1856	0.1224	0.1156	-0.304	-0.0167	-0.264	-0.1501	0.2181	0.2064	0.1018	1		
usm	0.0765	-0.1157	-0.4684	-0.2636	0.458	0.0513	-0.1022	-0.0447	0.1225	-0.0766	0.0384	0.0869	-0.1885	-0.3824	0.1365	-0.3901	1	
crisis	-0.0474	0.4449	-0.2822	0.0658	-0.0713	-0.3414	-0.0144	-0.0267	0.9154	0.0456	0.3145	-0.0756	-0.0511	0.1505	-0.0076	-0.2044	0.0379	1

Note: Variables are defined in Table 9.

Table 3.12 Multivariate Regressions

Variables	Model 1	Model 2	Model 3
POLICY	-0.0273 (1.15) [0.253]	-0.0343 (1.4) [0.164]	-0.0270 (1.1) [0.273]
GOVTOWN		-0.0238 (-1.61) [0.11]	-0.0253 (-1.63) [0.105]
NATRES		0.0103 (0.89) [0.373]	0.0093 (0.7) [0.482]
ITIN		-0.0279 (-2) [0.047]	-0.0255 (-1.86) [0.064]
THK			-0.0078 (-0.43) [0.669]
INDREL			-0.0126 (-1.33) [0.184]
ADVISOR			0.0036 (0.36) [0.722]
FEX			-0.0629 (-0.74) [0.461]
CASH			-0.0070 (-0.72) [0.475]
Constant	0.0066 (1.63) [0.106]	0.0231 (2.05) [0.042]	0.0394 (1.64) [0.104]
Observation	157	157	157

Variables	Model 1	Model 2	Model 3
F	1.32	1.46	0.71
Prob > F	0.2526	0.2166	0.6974
R-squared	0.0232	0.0715	0.0838

Note: The t-statistics are in parentheses and p-values are in brackets. We use White standard errors to calculate t-statistics. The dependent variable in the three models is CAR (-1,1).

Table 3.13 Comparison of Sample Means and Estimated Coefficients for Blinder-Oaxaca Decomposition

Panel A: Government Policy Variables

Variable	**Sample**	
	1994-2001	**2002-2009**
A. ***Sample means***		
CAR (-1,1)	0.0339	0.0066
GOVTOWN	0.5484	0.4524
NATRES	0.0323	0.3254
ITIN	0.3871	0.3254
B. ***Estimated coefficients***		
GOVTOWN	-0.1037 (-1.65) [0.111]	-0.0060 (-0.63) [0.533]
NATRES	-0.0940 (-4.03) [0]	0.0158 (1.36) [0.177]
ITIN	-0.1113 (-1.94) [0.063]	-0.0066 (-0.69) [0.488]
Constant	0.1369 (1.87) [0.072]	0.0064 (0.93) [0.352]

Variable	**Sample**	
	1994-2001	**2002-2009**
Observation	31	126
R-squared	0.2371	0.0335

Panel B: All Variables

Variables	Sample	
	1994-2001	**2002-2009**
A. Sample means		
CAR (-1,1)	0.0339	0.0066
GOVTOWN	0.5484	0.4524
NATRES	0.0323	0.3254
ITIN	0.3871	0.3254
THK	0.7419	0.2778
INDREL	0.2258	0.5952
ADVISOR	0.1613	0.3333
FEX	-0.0312	0.0553
CASH	0.4194	0.5952
B. Estimated Coefficients		
GOVTOWN	-0.0577 (-1.42) [0.17]	-0.0061 (-0.6) [0.546]

Variables	Sample	
	1994-2001	2002-2009
NATRES	-0.2381 (-2.25) [0.035]	0.0167 (1.39) [0.167]
ITIN	-0.1404 (-2.07) [0.051]	-0.0067 (-0.61) [0.542]
THK	-0.0764 (-0.95) [0.355]	0.0048 (0.4) [0.691]
INDREL	-0.1043 (-2.47) [0.022]	-0.0021 (-0.24) [0.807]
ADVISOR	-0.0328 (-1.03) [0.313]	0.0081 (0.8) [0.427]
FEX	2.5918 (2.36) [0.028]	0.0211 (0.35) [0.726]
CASH	-0.0434 (-1.18) [0.252]	0.0013 (0.17) [0.863]
Constant	0.3122 (1.98) [0.06]	0.0014 (0.14) [0.887]
Observation	31	126
R-squared	0.4427	0.044

Note: variables are defined in Table 9. Top part of each panel reports sample means. Bottom part reports results of regression when dependent variable is CAR(-1,1). T-statistics are listed in parentheses below estimated coefficients, and associated p-value are in brackets. White standard errors are used to calculate t-statistics.

Table 3.14 Decomposition of ACAR Gap

Panel A: Government Policy Variables

Policy Impact: 1994-2001/2002-2009 period					
Difference=-0.0273					
Variable	**GOVTOWN**	**NATRES**	**ITIN**	**Constant**	**Decomposition**
Mean_Diff(A)	-36.5	101.0	-25.2	0.0	39.3
Coef_Diff(A)	-161.9	-130.9	-124.9	478.3	60.7
Mean_Diff(B)	-2.1	-17.0	-1.5	0.0	-20.6
Coef_Diff(B)	-196.2	-13.0	-148.5	478.3	120.6

Note: Table 3.14 reports the results of applying the Blinder-Oaxaca decomposition to the difference in *ACAR* values in the pre- and post-Go Global periods. Changes in (i) mean sample characteristics, $\left(\overline{\boldsymbol{X}}_2 - \overline{\boldsymbol{X}}_1\right)$, and (ii) estimated coefficients, $\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$, are identified by "Means" and "Coefficients" respectively. The numbers in the table represent the percentage difference "explained" by the respective change for each variable, including changes in the estimated value of the constant term. A positive number suggests that the change contributed to the difference in *ACAR* values. A negative number suggests the opposite; namely, that the observed gap is smaller as a result of the respective change. We are looking for variables with large positive values for either "Means," "Coefficients," or both to identify the contributors to negative ACAR gap.

Panel B: All Variables

Policy Impact: 1994-2001/2002-2009 period										
Difference=-0.0273										
Variable	GOVTOWN	NATRES	ITIN	THK	INDREL	ADVISOR	FEX	CASH	Constant	Decomposition
Mean_Diff (A)	-20.3	255.7	-31.7	-129.9	141.2	20.7	-820.7	28.0	0.0	-557.0
Coef_Diff (A)	-85.5	-303.8	-159.3	-82.6	-222.9	-50.0	520.3	-97.5	1138.4	657.0
Mean_Diff (B)	-2.1	-18.0	-1.5	8.1	2.9	-5.1	-6.7	-0.8	0.0	-23.3
Coef_Diff (B)	-103.7	-30.1	-189.5	-220.6	-84.6	-24.2	-293.7	-68.7	1138.4	123.3

Note: Table 3.14 reports the results of applying the Blinder-Oaxaca decomposition to the difference in *ACAR* values in the pre- and post-Go Global periods. Changes in (i) mean sample characteristics, $\left(\overline{\boldsymbol{X}}_2 - \overline{\boldsymbol{X}}_1\right)$, and (ii) estimated coefficients, $\left(\hat{\boldsymbol{\beta}}_2 - \hat{\boldsymbol{\beta}}_1\right)$, are identified by "Means" and "Coefficients" respectively. The numbers in the table represent the percentage difference "explained" by the respective change for each variable, including changes in the estimated value of the constant term. A positive number suggests that the change contributed to the difference in *ACAR* values. A negative number suggests the opposite; namely, that the observed gap is smaller as a result of the respective change. We are looking for variables with large positive values for either "Means," "Coefficients," or both to identify the contributors to negative ACAR gap.

Table 4.1 Distribution of Chinese OMA Deals by Year

Year	No. of transactions	Deal with transaction value	Value of transaction (in mil USD)	Average transaction value (in mil USD)
1994	1	1	98.5	98.5
1995	1	1	1.3	1.3
1996	3	2	482.1	241
1997	4	3	360.6	120.2
1998	7	6	262.5	43.7
1999	5	3	45.9	15.3
2000	5	3	64	21.3
2001	6	4	50.5	12.6
2002	11	10	2098.9	209.9
2003	9	8	2057	257.1
2004	17	9	2267.9	252
2005	8	6	4243.6	707.3
2006	12	9	8511.9	945.8
2007	18	11	1716	156
2008	15	7	824.8	117.8
Total	122	83	23085.4	278.1

Note: Observations are those used for the three-year, long term performance.

Table 4.2 Distribution of Chinese OMA Deals by Region and Country

Country	Number of deals	Deal value available	Total value of deals ($mil)	Average Value of Deals ($mil)
Developed nations				
HK[18]	49	37	4507.8	121.8
US	12	10	2553.6	255.4
Australia	8	7	846.6	121
Canada	4	2	772.3	386.2
Germany	3	0	0	0
France	2	2	62	31
Japan	1	1	107	107
Netherlands	2	1	148.5	148.5
UK[19]	2	1	4141.2	4141.2
Singapore	6	2	980.9	490.4
South Korea	2	2	471.7	235.9
Sum	91	65	14591.6	224.5
Asia				
Indonesia	5	4	1129.5	282.4
Kazakhstan	2	1	200	200
India	2	1	1.1	1.1
Azerbaijan	2	2	70	35
Pakistan	1	1	284	284
Russian Fed	2	2	3600	1800
Malaysia	1	1	11.5	11.5
Philippines	1	1	70	70
Sum	16	13	5366.1	412.8
Africa				
Nigeria	2	1	2692	2692
Chad	1	1	202.5	202.5
Sum	3	2	2894.5	1447.3

Country	Number of deals	Deal value available	Total value of deals ($mil)	Average Value of Deals ($mil)
South America				
British Virgin	3	2	33.2	16.6
Peru	2	1	200	200
Sum	5	3	233.2	77.7
Others[20]	7	0	0	0
Total	122	83	23085.4	278.1

Note: Observations are those used for the three-year, long term performance.

[18] We include Hong Kong targets in the overseas M&A group because most researchers argue that Hong Kong has obviously different economic system away from Chinese mainland.
[19] Both of the target firms are PetroKazakhstan and with the nationality of United Kingdom in SDC database because they argue that the headquarter of PetroKazakhstan is in the United Kingdom. However, most Chinese consider it as a Canadian firm. In Zephyr M&A database, the nationality of PetroKazakhstan is Canada too.
[20] Others include Chinese OMAs in Mexico, Mongolia, Portugal, Tunisia, Vietnam, Zambia and Thailand.

Table 4.3 Industry Distribution of Chinese OMAs

Target industry	1994-2008		1994-2001		2002-2008	
	Total Deals	Average value	Deals[21]	Average value	Deals	Average value
Telecommunication and Electronics, Prepacked Software[22]	32	191.4	11 (34%)	16	21 (23%)	263.6
Energy and Natural Resources[23]	31	669.7	2 (6%)	0	29 (32%)	669.7
Wholesales and Retail Trade[24]	10	67.2	4 (13%)	81.6	6 (7%)	48.1
Miscellaneous Manufacturing Products[25]	13	44	4 (13%)	9.9	9 (10%)	78.2
Transportation[26]	9	245.1	3 (9%)	279.2	6 (7%)	228.1
Miscellaneous Business Services[27]	14	163	2 (6%)	8.7	12 (13%)	201.4
Chemicals and Drugs[28]	4	29.8	2 (6%)	1.3	2 (2%)	58.2
Electric, Gas and Water Distribution, Construction	9	93.9	4 (13%)	13.3	5 (6%)	214.8
Total	122	278.1	32 (100%)	59.3	90 (100%)	362

Note: Observations are those used for the three-year, long term performance.

[21] The percentage in the brackets shows the proportion in total deals in the period.

[22] "Telecommunication and Electronics, Prepackaged Software Industry" consists of the following SDC categories: "Computer and Office Equipment;" "Telecommunications;" "Electronic and Electrical Equipment;" "Communications Equipment;" and "Prepackaged Software."

[23] "Energy and Natural Resources" consists of the following SDC categories: "Oil and Gas;" "Petroleum Refining;" "Mining;" "Metal and Metal Products;" and "Agriculture, Forestry, and Fishing."

[24] "Wholesale, Retail, Trade" consists of the following SDC categories: "Wholesale Trade-Nondurable Goods;" "Wholesale Trade-Durable Goods;" and "Miscellaneous Retail Trade."

[25] "Miscellaneous Manufacturing Products" consists of the following SDC categories: "Measuring, Medical, Photo Eqipment;" "Clocks;" "Food and Kindred Products;" "Stone, Clay, Glass, and Concrete Products;" "Textile and Apparel Products;" "Wood Products, Furniture, and Fixtures;" "Machinery;" "Miscellaneous Manufacturing;" and "Transportation Equipment."

[26] "Transportation" consists of the following SDC categories: "Transportation and Shipping (except Air);" and "Air Transportation and Shipping."

[27] "Miscellaneous Business Services" consists of the following SDC categories: "Business Services;" "Health Services;" "Investment and Commodity Firms, Dealers, Exchanges;" and "Radio and Television Broadcasting Stations."

[28] "Chemicals and Drugs" consists of the following SDC categories: "Drugs;" and "Chemicals and Allied Products."

Table 4.4 Long-Term Performance of Chinese OMAs, 1994-2008

	6 month	12 month	18 month	24 month	30 month	36 month
CTAR	0.054	0.052	0.056	0.028	-0.012	-0.015
t	0.596	0.406	0.362	0.146	-0.07	-0.1
p-value	0.551	0.685	0.717	0.884	0.944	0.92
Observation	119	119	120	120	94	94

Note: $CTAR = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} CTAR_{it}$, where $CTAR_{it}$ is defined in Equation 1.

Table 4.5A Reproduction of Fama and French (1993) Results

Dependent variable: Excess returns on 25 stock portfolios formed on size and book-to-market equity										
	Book-to-market equity (BE/ME) quintiles									
Size quintile	Low	2	3	4	High	Low	2	3	4	High
	a					*t(a)*				
Small	-0.34	-0.12	-0.05	0.01	0.00	-3.16	-1.47	-0.73	0.22	0.14
2	-0.11	-0.01	0.08	0.03	0.02	-1.24	-0.20	1.04	0.51	0.34
3	-0.11	0.04	-0.04	0.05	0.05	-1.42	0.47	-0.47	0.71	0.56
4	0.09	-0.22	-0.08	0.03	0.13	1.07	-2.65	-0.99	0.33	1.24
Big	0.21	-0.05	-0.13	-0.05	-0.16	3.27	-0.67	-1.46	-0.69	-1.41
	b					*t(b)*				
Small	1.04	1.02	0.95	0.91	0.96	39.37	51.80	60.44	59.73	57.89
2	1.11	1.06	1.00	0.97	1.09	52.49	61.18	55.88	61.54	65.52
3	1.12	1.02	0.98	0.97	1.09	56.88	53.17	50.78	54.38	52.52
4	1.07	1.08	1.04	1.05	1.18	53.94	53.51	51.21	47.09	46.10
Big	0.96	1.02	0.98	0.99	1.06	60.93	56.76	46.57	53.87	38.61
	s					*t(s)*				
Small	1.46	1.26	1.19	1.17	1.23	37.92	44.11	52.03	52.85	50.97
2	1.00	0.98	0.88	0.73	0.89	32.73	38.79	34.03	31.66	36.78
3	0.76	0.65	0.60	0.48	0.66	26.40	23.39	21.23	18.62	21.91
4	0.37	0.33	0.29	0.24	0.41	12.73	11.11	9.81	7.38	11.01
Big	-0.17	-0.12	-0.23	-0.17	-0.05	-7.18	-4.51	-7.58	-6.27	-1.18
	h					*t(h)*				
Small	-0.29	0.08	0.26	0.40	0.62	-6.47	2.35	9.66	15.53	22.24
2	-0.52	0.01	0.26	0.46	0.70	-14.57	0.41	8.56	17.24	24.80
3	-0.38	-0.00	0.32	0.51	0.68	-11.26	-0.05	9.75	16.88	19.39
4	-0.42	0.04	0.30	0.56	0.74	-12.51	1.04	8.83	14.84	17.09
Big	-0.46	0.00	0.21	0.57	0.76	-17.03	0.09	5.80	18.34	16.24
	R^2					*s(e)*				
Small	0.94	0.96	0.97	0.97	0.96	1.94	1.44	1.16	1.12	1.22
2	0.95	0.96	0.95	0.95	0.96	1.55	1.27	1.31	1.16	1.23
3	0.95	0.94	0.93	0.93	0.93	1.45	1.41	1.43	1.32	1.52
4	0.94	0.93	0.91	0.89	0.89	1.46	1.48	1.49	1.63	1.88
Big	0.94	0.92	0.88	0.90	0.83	1.16	1.32	1.55	1.36	2.02

Note: Taken from Tables 6 and 9a in Fama and French (1993). The estimates come from estimation of the following equation: $R(t)-RF(t)=a+b[RM(t)-RF(t)]+sSMB(t)+hHML(t)+e(t)$

Table 4.5B FF3FM Results for 16 Portfolios

Size quintile	Book-to-market quintiles				Book-to-market quintiles			
	Low	2	3	High	Low	2	3	High
	Alpha				**Beta**[29]			
Small	0.1035	0.1202	0.1190	0.3749	1.1058	1.0498	1.3393	1.2169
2	0.0638	-0.0648	0.0942	0.3269	1.0906	0.9691	1.3795	1.1123
3	0.3269	0.4193	0.2591	0.0926	1.4225	1.3977	1.1536	1.0154
Big	0.1975	-0.0262	0.1765	-0.0149	1.1011	0.7921	1.0927	0.8784
	t (Alpha)				*t* (Beta)			
Small	1.7017	1.8671	6.7906	3.6563	1.1698	0.4193	1.6246	1.1877
2	0.7365	-0.7434	1.7445	4.1418	0.3863	-0.1780	1.1718	1.1419
3	4.0799	10.4529	4.6676	7.8730	1.8797	2.8456	2.7328	0.1929
Big	6.0027	-0.5725	5.2713	-0.4929	0.6772	-1.5269	1.6324	-1.1632
	p (Alpha)				*p* (Beta)			
Small	0.0888	0.0619	0.0000	0.0003	0.2421	0.6750	0.1043	0.2349
2	0.4614	0.4572	0.0811	0.0000	0.6993	0.8587	0.2413	0.2535
3	0.0000	0.0000	0.0000	0.0000	0.0601	0.0044	0.0063	0.8470
Big	0.0000	0.5670	0.0000	0.6221	0.4983	0.1268	0.1026	0.2447
	S				**H**			
Small	0.8642	0.2375	-0.0632	0.2868	-0.7151	0.0215	-0.1132	0.8826
2	0.0248	-0.1260	0.1412	0.0977	-0.1979	-0.0108	-0.0222	0.1274
3	-0.4033	0.0483	0.3779	0.1020	0.2448	-0.0324	-0.0357	0.0422
Big	-0.1115	-0.8525	-0.0109	-0.3300	-0.0157	-0.1323	0.1216	-0.1584
	t (s)				*t* (h)			
Small	2.0009	1.7791	-0.1358	0.7260	-1.1927	0.1131	-0.4348	2.3515
2	0.1819	-0.8436	0.2045	1.5811	-1.9624	-0.0978	-0.0892	0.6023
3	-1.8652	0.3453	1.5507	0.3433	2.0119	-0.3027	-0.2184	0.4211
Big	-1.2606	-4.0619	-0.1167	-2.3033	-0.2026	-0.4222	2.3160	-1.2419
	p (s)				*p* (h)			
Small	0.0454	0.0752	0.8920	0.4679	0.2330	0.9100	0.6637	0.0187
2	0.8557	0.3989	0.8380	0.1139	0.0497	0.9221	0.9289	0.5470
3	0.0622	0.7299	0.1210	0.7314	0.0442	0.7621	0.8271	0.6737
Big	0.2074	0.0000	0.9071	0.0213	0.8395	0.6729	0.0206	0.2143
	R^2				**Portfolio N**			
Small	0.3673	0.5305	0.5565	0.4162	7	3	3	7
2	0.4305	0.5596	0.6611	0.6818	5	8	3	9
3	0.7103	0.7120	0.7480	0.6118	5	11	6	4
Big	0.6702	0.4673	0.6937	0.6240	8	3	12	4

Note: Time series regressions with T=41 months.

[29] The hypothesis test for beta (H_{10}): Beta=1. We also tested the hypothesis for beta (H_{20}): Beta=0 and got very large *t* values for all 16 portfolio Betas, suggesting to reject Beta=0 at 1% level.

Table 4.6 Performance Breakdown by Year

Year	CAR (-1,1)	Year 1 CTAR	Year 2 CTAR	Year 3 CTAR
1994	0.02	-0.36	-0.02	0.13
1995	-0.01	0.26	0.07	-0.05
1996	0.04	0.44	0.42	0.06
1997	0.14	-0.26	-0.58	-0.16
1998	0.03	-0.30	-0.28	-0.26
1999	0.03	0.44	-0.01	-0.22
2000	0.03	0.13	-0.01	0.10
2001	-0.01	0.12	0.65	0.06
2002	0.01	0.02	0.12	0.07
2003	-0.01	0.01	0.01	-0.06
2004	0.01	-0.10	-0.19	0.00
2005	0.00	0.09	0.03	0.08
2006	-0.01	0.14	0.06	-0.07
2007	0.03	0.12	0.11	0.16
2008	-0.01	0.22	0.17	n.a.
1994-2001				
Mean	0.04	0.02	0.00	-0.08
Median	0.00	0.04	0.04	0.05
Std. Dev	0.02	-0.06	-0.02	-0.04
2002-2008				
Mean	0.00	0.02	0.08	0.04
Median	0.13	0.60	0.67	0.31
Std. Dev	0.03	0.30	0.28	0.15
1994-2008				
Mean	0.01	0.05	0.03	-0.01
Median	0.00	0.02	0.04	0.02
Std. Dev	0.07	0.40	0.43	0.23

Table 4.7 Long-Term Performance in Different Markets

Interval (In months)	Chinese Mainland			Hong Kong			U.S.		
	CTAR	***t***	***p-value***	**CTAR**	***t***	***p-value***	**CTAR**	***t***	***p-value***
6 month	0.0223	0.3173	0.7511	-0.0415	-0.5651	0.5720	0.1905	1.2624	0.2068
12 month	0.0682	0.5433	0.5869	-0.0433	-0.3468	0.7287	0.1046	0.4896	0.6244
18 month	0.0843	0.4917	0.6230	-0.0232	-0.1664	0.8678	0.0751	0.3108	0.7560
24 month	0.0082	0.0423	0.9662	-0.0105	-0.0617	0.9508	0.0455	0.1444	0.8852
30 month	-0.0322	-0.1208	0.9039	-0.0047	-0.0256	0.9796	0.0266	0.1038	0.9174
36 month	-0.0068	-0.0291	0.9768	0.0042	0.0229	0.9818	0.0087	0.0422	0.9664
Observation	50			68			64		

Table 4.8A Performance Breakdown by Sectors

Target sector	Deal Number	CAR (-1,1)	Year 1 CTAR	Year 2 CTAR	Year 3 CTAR
Telecommunication and Electronics, Prepacked Software	32	0.00	0.18	0.14	0.03
Energy and Natural Resources	31	0.00	0.12	0.02	0.08
Wholesale and Retail Trade	10	0.10	1.80	-0.27	-0.24
Miscellaneous Manufacturing Products	13	0.03	0.54	0.10	0.05
Transportation	9	0.00	0.29	0.07	0.01
Miscellaneous Business Services	14	0.00	0.08	0.08	0.18
Chemicals and Drugs	4	0.00	-0.12	0.15	-0.06
Electric, Gas and Water Distribution, Construction	9	0.00	0.24	0.01	-0.06
Mean		*0.01*	*0.05*	*0.03*	*-0.01*
Median		*0.00*	*0.02*	*0.04*	*0.02*
Standard deviation		*0.07*	*0.40*	*0.43*	*0.23*

Table 4.8B Sector Performance

Target Sector	CAR(-1,1)	Y1CTAR	Y2CTAR	Y3CTAR
Telecommunication and Electronics, Prepacked Software	-0.0117 (-0.9500) [0.3420]	0.1252 (1.1100) [0.2700]	-0.0006 (-0.0100) [0.9960]	-0.0062 (-0.1000) [0.9200]
Energy and Natural Resources	-0.0139 (-1.2800) [0.2040]	-0.0416 (-0.6600) [0.5130]	0.0640 (0.8800) [0.3830]	0.0853 (1.9800) [0.0510]
Wholesale and Retail Trade	0.0935 (1.4600) [0.1470]	-0.3530*** (-3.9700) [0.0000]	-0.2894** (-2.1500) [0.0340]	-0.0167 (-0.2000) [0.8410]
Miscellaneous Manufacturing Products	0.0215 (0.8400) [0.4010]	0.0592 (0.5900) [0.5540]	0.0200 (0.2300) [0.8180]	-0.0733 (-0.5200) [0.6010]
Transportation	-0.0168 (-0.7000) [0.4830]	0.0154 (0.1300) [0.8930]	-0.0210 (-0.1600) [0.8690]	-0.0444 (-1.0700) [0.2870]

Target Sector	**CAR(-1,1)**	**Y1CTAR**	**Y2CTAR**	**Y3CTAR**
Miscellaneous Business Services	-0.0153 (-1.5300) [0.1300]	0.0340 (0.4600) [0.6480]	0.1758 (1.3200) [0.1890]	-0.0426 (-0.5200) [0.6050]
Chemicals and Drugs	-0.0177 (-1.9700) [0.0520]	0.1017 (0.8300) [0.4070]	-0.0901 (-1.2700) [0.2050]	-0.0390 (-0.8900) [0.3730]
Electric, Gas and Water Distribution, Construction	-0.0101 (-0.8700) [0.3880]	-0.0394 (-0.4500) [0.6570]	-0.0926 (-1.1300) [0.2620]	0.0159 (0.2900) [0.7730]
Observation	114	119	120	94

Note: the value in the parentheses is the *t*-statistic, and the value in brackets is the *p*-value. *t*-statistics are calculated from White robust standard errors.

Table 4.9 Performance of Top 15 Chinese Overseas M&As, 1994-2010

Acquirer Name	Year	Target Name	Target Nation	Target Industry	Shares Acq. (%)	Transaction Value ($mil)	CAR (-1,1)	Year 3 CTAR	Acquirer Advisors
CNPC	2005	PetroKaza -khstan	UK	Energy	100	4141.2	-0.025	0.124	Citigroup
Sinopec	2006	OAO Udmurtneft	Russian	Energy	96.9	3500	0.003	0.044	Dresdner Kleinwort Wasserstein
Yanzhou Coal Mining	2009	Felix Resources	Australia	Mining	100	2806.9	n.a.[30]	n.a.[31]	UBS Investment Bank
CNOOC Ltd	2006	NNPC-OML 130	Nigeria	Energy	45	2692	0.005	0.333	Goldman Sachs & Co
Lenovo Group	2005	IBM Corp Personal Computing	US	Hi-Tech	100	1750	0.027	0.255	Goldman Sachs (Asia) Cazenove Asia Ltd BNP Paribas SA
PetroChina	2010	Athabasca Oil Sands-Assets	Canada	Energy	60	1737	n.a.[32]	n.a.[33]	TD Securities Inc
China Unicom	2003	Unicom New World (BVI)Ltd	HK	Hi-Tech	100	1368.1	-0.018	-0.194	Lehman Brothers Asia China International Capital Co
Bank of China	2006	Singapore Aircraft Leasing	Singa- -pore	Business Services	100	965	n.a.[34]	-0.131	Morgan Stanley UBS Investment Bank Bank of China International
Aluminium Corp of China	2007	Peru Copper Inc	Canada	Mining	100	770.785	-0.0048	0.1959	BMO Capital Markets

Acquirer Name	Year	Target Name	Target Nation	Target Industry	Shares Acq. (%)	Transaction Value ($mil)	CAR (-1,1)	Year 3 CTAR	Acquirer Advisors
Air China Ltd	2006	Cathay Pacific Airways	HK	Transpor-tation	10.16	694.538	-0.0069	0.0041	Merrill Lynch China International Capital Co BNP Paribas SA
CNOOC Ltd	2002	Repsol YPF SA	Indo -nesia	Energy	100	591.86	0.0498	0.0416	Merrill Lynch (Asia Pacific)
CNOOC Ltd	2004	North West Shelf Gas Pty	Australia	Energy	5.3	537.308	-0.0180	-0.1046	Merrill Lynch Credit Suisse First Boston
China Resources Entrp	4/12/ 1996	Hong Kong Intl Terminal	HK	Transpor-tation	10	476.988	0.1197	0.0334	n.a
Wuhan Iron & Steel	2010	MMX Sudeste Mineracao SA	Brazil	Mining	21.52	400	n.a.[35]	n.a.[36]	BNP Paribas SA
BOE	2003	Hydis	South Korea	Hi-Tech	100	380	0.0213	0.1859	n.a

[30] The CAR(-1,1) value is missing here because we delete observations with more than 50% zero return in investigation period.
[31] The Year 3 CTAR value is missing here because the missing of time series returns data in the third year after OMA (2010).
[32] The CAR(-1,1) value is missing here because we delete observations with more than 50% zero return in investigation period.
[33] The Year 3 CTAR value is missing here because the missing of three years time series returns data after OMA.
[34] The CAR(-1,1) value is missing here because we delete observations with more than 50% zero return in investigation period.
[35] The CAR(-1,1) value is missing here because we delete observations with more than 50% zero return in investigation period.
[36] The Year 3 CTAR value is missing here because the missing of three years time series returns data after OMA.

Table 4.10 Variable Descriptions

Dependent variable	**Y3CTAR, cumulative three years calendar time abnormal return after effective date**
Independent variables	Description
CAR3	Cumulated abnormal return from day (-1) to day (1) in test period
Y1CTAR	Cumulated one years calendar time abnormal return after effective date
Y2CTAR	Cumulated two years calendar time abnormal return after effective date
CULDIS	Culture difference scores between China and the targets[37]
FEX	US dollar depreciation according to Chinese RMB[38]
DEVDC	Dummy 1 if target is in developed country, 0 if not
THK	Dummy 1 if HK target, 0 if not
INDREL	Dummy 1 if related (SIC 2-digit code), 0 if unrelated
GOVTOWN	Dummy 1 if Government owned enterprises, 0 if not[39]
CASH	Dummy 1 if cash payment, 0 if stock exchange
NATRES	Dummy 1 if natural resources industry targets, 0 if not
ITIN	Dummy 1 if technology-intensive targets, 0 if not
TRAVALUE	Transaction value of the deal, in USD million
LNTRAVALUE	Log form of transaction value
MV24a	Market value 24 months after effective
LNMV24a	Log form of market value 24 months after effective
Y2BM	Book to market ratio two years after effective
ADVISOR	Dummy 1 if acquirer employed institutional advisor, 0 if not
HKM	Dummy 1 if list in Hong Kong market, 0 if not
USM	Dummy 1 if list in US market, 0 if not
POLICY	Dummy 1 if year after China Go Global Policy, 0 if not
SECTOR	Control groups include 8 sectors reported in Table 3 and Table 8

37 Hofstede's Cultural dimensions scores are from http://www.geert-hofstede.com. The culture distance index equation from Kogut and Sing (1998) is:

$$CD_j = \sum_{i=1}^{4} \frac{\{(I_{ij} - I_{iN})^2 / V_i\}}{4}$$

Where CD_j indicates the culture distance index between country j and the home country;

I_{ij} indicates culture dimension score on ith item of country j;

I_{iN} indicates culture distance dimension score of home country while

V_i is the variance of culture distance dimension scores.

[38] FEX is computed as following:

$$FEX = \frac{\frac{1}{n}\sum_{i=1}^{n} e_k - e_{ak}}{\frac{1}{n}\sum_{i=1}^{n} e_k}$$

e_k indicates the daily exchange rate of USD (units of dollars per unit of RMB) in the year 1994-2007;

e_{ak} indicates daily foreign exchange rate of the USD in the year of the announcement,

Positive FEX_k values indicate a cheaper dollar for the Chinese acquirers, while negative values indicate that the USD will be more expensive.

[39] Government owned enterprise is defined when the ultimate parent company is government owned in SDC Platinum.

Table 4.11 Summary Statistics for Performance Determinants

Variable	Obs	Mean	Std. Dev.	Min	Max
CAR(-1,1)	114	0.0131	0.0749	-0.1380	0.6316
Y1CTAR	119	0.0517	0.4026	-0.8172	2.7705
Y2CTAR	120	0.0280	0.4276	-1.2233	2.4042
Y3CTAR	94	-0.0146	0.2345	-1.2320	0.3954
CULDIS	111	1.2873	1.3858	0.1400	4.5890
FEX	122	0.0208	0.0575	-0.0242	0.1593
DEVDC	122	0.7541	0.4324	0.0000	1.0000
THK	122	0.4016	0.4923	0.0000	1.0000
INDREL	122	0.5000	0.5021	0.0000	1.0000
GOVTOWN	122	0.5000	0.5021	0.0000	1.0000
POLICY	122	0.7377	0.442	0.0000	1.0000
CASH	122	0.5410	0.5004	0.0000	1.0000
NATRES	122	0.2541	0.4371	0.0000	1.0000
ITIN	122	0.3361	0.4743	0.0000	1.0000
TRAVALUE	83	278.1367	691.4977	0.6000	4141.179
LNTRAVALUE	83	3.7895	2.0447	-0.5108	8.3287
MV24a	116	20715.59	53576.4	2.1800	331338.4

Variable	Obs	Mean	Std. Dev.	Min	Max
LNMV24a	116	7.5855	2.3998	0.7793	12.7109
Y2BM	108	0.5549	0.9104	0.0004	8.1726
ADVISOR	122	0.2951	0.4580	0.0000	1.0000
HKM	122	0.4180	0.4953	0.0000	1.0000
USM	122	0.1885	0.3927	0.0000	1.0000

Table 4.12 Correlation Coefficients

	y3ctar	market	culdis	fex	devdc	thk	indrel	govtown	cash	natrel	itin	travalue	mv24a	y2bm	policy	advisor
y3ctar	1.0000															
market	-0.0857	1.0000														
culdis	0.0195	-0.0223	1.0000													
fex	0.1061	-0.0375	0.2927	1.0000												
devdc	-0.1663	0.0739	0.0955	-0.1178	1.0000											
thk	-0.1557	0.1147	-0.7394	-0.3136	0.4678	1.0000										
indrel	0.2356	-0.0781	0.1027	-0.0365	-0.0761	-0.1505	1.0000									
govtown	0.0169	-0.2566	-0.2124	-0.2838	-0.2284	0.0502	0.1148	1.0000								
cash	0.0692	-0.1226	-0.0284	-0.0166	0.0088	0.0501	0.1645	0.0987	1.0000							
natrel	0.1594	-0.2472	0.2099	0.0161	-0.4537	-0.4398	0.2071	0.3954	0.1220	1.0000						
itin	-0.0539	0.3873	-0.0445	0.0135	0.2048	0.2312	0.0868	-0.3297	-0.1107	-0.4152	1.0000					
travalue	0.1580	-0.0892	0.1647	-0.0148	-0.1483	-0.2040	0.1439	0.2441	0.0418	0.3210	-0.1081	1.0000				
mv24a	0.0182	-0.2030	0.0024	0.1565	-0.1459	-0.0669	0.0426	0.3352	0.0495	0.1371	-0.0856	0.2930	1.0000			
y2bm	-0.1159	0.1911	0.0698	-0.0393	0.0257	-0.0312	-0.1930	-0.0350	-0.1549	-0.0630	-0.0544	-0.1111	-0.1025	1.0000		
policy	0.1867	-0.2424	0.2637	0.4198	-0.2107	-0.3477	0.2981	-0.0373	0.1986	0.2624	-0.0491	0.1971	0.2066	-0.0792	1.0000	
advisor	-0.0370	0.0826	0.0934	-0.0383	0.1190	-0.0535	0.1797	0.1438	0.1992	0.0765	0.0343	0.4281	0.1869	-0.1178	0.1815	1.0000

Table 4.13 Univariate Regression of Determinants of Long-Term OMA Performance

Variables	YEAR1 CTAR	YEAR2 CTAR	YEAR3 CTAR
CAR (-1,1)	-0.3101 (-0.5600) [0.5760]	-1.2769 (-2.2200) [0.0290]	-0.7068 (-1.2900) [0.1990]
Y1CTAR	---	---	---
Y2CTAR	0.4799 (3.4200) [0.0010]	---	---
Y3CTAR	---	0.1651 (2.5500) [0.0130]	---
CULDIS	0.0394 (1.4100) [0.1600]	-0.0306 (-0.9800) [0.3300]	0.0034 (0.2100) [0.8370]
FEX	1.2515 (2.0300) [0.0450]	1.3024 (2.3500) [0.0210]	1.0324 (1.2500) [0.2140]
DEVDC	-0.0134 (-0.2100) [0.8370]	-0.1248 (-1.9200) [0.0570]	-0.0916 (-1.9600) [0.0530]
THK	-0.0769 (-0.9500) [0.3450]	0.0165 (0.2000) [0.8430]	-0.0729 (-1.4500) [0.1510]
INDREL	0.0120 (0.1600) [0.8720]	0.0094 (0.1200) [0.9050]	0.1100 (2.2700) [0.0250]
GOVTOWN	-0.1143 (-1.5700) [0.1200]	-0.0688 (-0.8700) [0.3850]	0.0080 (0.1500) [0.8830]

Variables	**YEAR1 CTAR**	**YEAR2 CTAR**	**YEAR3 CTAR**
POLICY	0.0459 (0.4100) [0.6820]	0.0337 (0.2700) [0.7860]	0.0926 (1.5400) [0.1280]
CASH	0.0004 (0.0000) [0.9960]	0.0072 (0.0900) [0.9300]	0.0325 (0.6600) [0.5080]
NATREL	-0.0416 (-0.6600) [0.5130]	0.0640 (0.8800) [0.3830]	0.0853 (1.9800) [0.0510]
ITIN	0.1460 (1.5800) [0.1160]	0.1202 (1.2400) [0.2180]	-0.0270 (-0.4900) [0.6240]
LNTRAVALUE	0.0095 (0.6100) [0.5420]	0.0222 (0.8100) [0.4220]	0.0158 (1.1200) [0.2650]
LNMV	-0.0098 (-0.2900) [0.7710]	0.0141 (0.5100) [0.6100]	0.0182 (1.4900) [0.1400]
BM	-0.1159 (-2.6700) [0.0090]	-0.0732 (-2.1900) [0.0300]	-0.0223 (-1.8000) [0.0760]
ADVISOR	-0.1413 (-2.0700) [0.0410]	-0.0876 (-1.1600) [0.2470]	-0.0184 (-0.4100) [0.6860]
HKM	-0.2095 (-3.0800) [0.0030]	-0.0676 (-0.9200) [0.3580]	0.0158 (0.3200) [0.7480]
USM	0.2896 (1.9500) [0.0540]	0.1728 (0.9800) [0.3300]	-0.0700 (-0.8100) [0.4190]

Note: Numbers in parentheses are *t*-statistics, numbers in brackets are *p*-values. *t*-statistics are calculated from White heteroscedasticity robust standard errors.

Table 4.14A Determinants of Chinese OMA Performance

Variable	Model 1	Model 2	Model 3	Model 4
Constant	0.3625 (2.33) [0.03]	0.3623 (2.39) [0.02]	0.2790 (4.84) [0.00]	0.1215 (1.90) [0.06]
GOVTOWN	-0.2185 (-3.20) [0.00]	-0.2168 (-3.30) [0.00]	-0.1284 (-2.42) [0.02]	-0.1058 (-2.21) [0.03]
Y2BM	-0.0297 (-1.71) [0.10]	-0.0303 (-1.89) [0.07]	-0.0153 (-1.19) [0.24]	-0.0185 (-1.24) [0.22]
CULDIS	-0.0651 (-1.40) [0.17]	-0.0653 (-1.43) [0.16]	-0.0491 (-2.45) [0.02]	
FEX	2.9877 (2.49) [0.02]	2.9892 (2.53) [0.02]	1.0579 (1.62) [0.11]	
DEVDC	0.0809 (0.64) [0.53]	0.0813 (0.66) [0.52]	-0.0278 (-0.48) [0.64]	
THK	-0.1001 (-0.72) [0.48]	-0.0999 (-0.73) [0.47]	-0.1153 (-1.52) [0.13]	
INDREL	0.1245 (1.60) [0.12]	0.1236 (1.59) [0.12]		
CASH	-0.1902 (-1.67) [0.11]	-0.1942 (-2.08) [0.05]		
LNTRAVALUE	0.0010 (0.05) [0.96]	0.0007 (0.04) [0.97]		

Variable	Model 1	Model 2	Model 3	Model 4
ADVISOR	-0.1284 (-1.61) [0.12]	-0.1286 (-1.63) [0.11]		
LNMV24A	0.0193 (1.05) [0.30]	0.0193 (1.07) [0.29]		
HKM	0.0890 (2.10) [0.04]	0.0891 (2.16) [0.04]		
USM	0.1736 (1.82) [0.08]	0.1757 (1.85) [0.07]		
ITIN	-0.0155 (-0.18) [0.86]	-0.0159 (-0.19) [0.85]		
POLICY	-0.0072 (-0.11) [0.92]			-0.0012 (-0.02) [0.99]
TRADE	-0.3489 (-2.87) [0.01]	-0.3491 (-2.93) [0.01]	-0.0743 (-0.89) [0.38]	-0.0537 (-0.57) [0.57]
ENERGY	-0.0432 (-0.50) [0.62]	-0.0451 (-0.54) [0.59]	0.0079 (0.14) [0.89]	0.0531 (0.99) [0.33]
TELECOM	-0.2959 (-2.25) [0.03]	-0.2978 (-2.38) [0.02]	-0.0648 (-0.95) [0.35]	-0.0754 (-1.09) [0.28]
SERVICE	-0.2738 (-2.20) [0.04]	-0.2759 (-2.35) [0.03]	-0.1048 (-1.31) [0.20]	-0.1300 (-1.56) [0.12]
UTILITIES	-0.1015 (-1.52) [0.14]	-0.0988 (-1.47) [0.15]	-0.0168 (-0.34) [0.73]	-0.0128 (-0.25) [0.81]

Variable	Model 1	Model 2	Model 3	Model 4
TRANSPORTATION	-0.1903 (-2.45) [0.02]	-0.1912 (-2.65) [0.01]	-0.0523 (-0.98) [0.33]	-0.0720 (-1.55) [0.13]
CHEMICAL	-0.0625 (-0.50) [0.62]	-0.0656 (-0.58) [0.57]	-0.0732 (-2.16) [0.03]	-0.1087 (-2.86) [0.01]
Obs	55	55	75	82
R-sq	0.5521	0.5519	0.1931	0.1194
F			5.06	4.83
Prob>F			0	0

Note: The dependent variables in Models 1-4 are 3-year calendar-time abnormal returns (Y3CTARs). Models 1-4 are fixed effects models with fixed group on sector variable. Numbers in parentheses are *t*-statistics. Numbers in brackets are *p*-values. *t*-statistics are calculated from White heteroscedasticity robust standard errors.

Table 4.14B Determinants of Chinese OMA Performance

Variable	Model 5	Model 6	Model 7	Model 8
Constant	0.2263 (1.83) [0.07]	-0.0407 (-0.37) [0.71]	0.0788 (1.64) [0.11]	0.1206 (4.10) [0.00]
GOVTOWN	-0.1220 (-2.75) [0.01]	-0.1908 (-3.34) [0.00]	-0.1045 (-2.34) [0.02]	-0.1056 (-2.49) [0.02]
Y2BM	-0.0201 (-1.24) [0.22]	0.0010 (0.04) [0.97]	-0.0222 (-2.06) [0.04]	-0.0185 (-1.27) [0.21]
CULDIS				
FEX				
DEVDC				
THK				
INDREL	0.0994 (1.40) [0.17]			
CASH	-0.0861 (-0.91) [0.37]			
LNTRAVALUE	0.0088 (0.58) [0.57]			
ADVISOR	-0.0537 (-0.78) [0.44]			

Variable	Model 5	Model 6	Model 7	Model 8
LNMV24A		0.0271 (1.55) [0.13]		
HKM		0.0489 (1.20) [0.23]		
USM		0.0018 (0.01) [0.99]		
ITIN			-0.0517 (-0.94) [0.35]	
NATRES			0.0948 (2.36) [0.02]	
POLICY				
TRADE	-0.2395 (-2.10) [0.04]	-0.0931 (-0.92) [0.36]		-0.0535 (-0.57) [0.57]
ENERGY	-0.0399 (-0.54) [0.59]	-0.0027 (-0.04) [0.97]		0.0525 (1.31) [0.20]
TELECOM	-0.1576 (-1.30) [0.20]	-0.1044 (-1.40) [0.17]		-0.0754 (-1.09) [0.28]
SERVICE	-0.1659 (-1.60) [0.12]	-0.1828 (-2.07) [0.04]		-0.1301 (-1.57) [0.12]
UTILITIES	-0.1090 (-1.52) [0.14]	-0.0191 (-0.29) [0.77]		-0.0126 (-0.26) [0.80]

Variable	Model 5	Model 6	Model 7	Model 8
TRANSPORTATION	-0.1423 (-2.27) [0.03]	-0.0909 (-1.75) [0.08]		-0.0721 (-1.60) [0.11]
CHEMICAL	-0.1141 (-1.76) [0.09]	-0.1206 (-2.76) [0.01]		-0.1092 (-4.26) [0.00]
Obs	60	82	82	82
R-sq	0.2464	0.1806	0.1006	0.1194
F		3.99	4.73	5.4
Prob>F		0.0001	0.0018	0

Note: The dependent variables in Models 5-8 are 3-year calendar-time abnormal returns (Y3CTARs). Models 5,6 and 8 are fixed effects models with fixed group on sector variable. Model 7 is simple OLS regression. Numbers in parentheses are *t*-statistics. Numbers in brackets are *p*-values. *t*-statistics are calculated from White heteroscedasticity robust standard errors.

Table 5.1 Summary Information on Multi-listings

Listing	Number of firms	Number of events	Number of observations
China only	40	50	50
Hong Kong only	22	30	30
U.S. only	17	31	31
China and Hong Kong	4	6	12
China and U.S.	0	0	0
Hong Kong and U.S.	9	30	60
China, Hong Kong and U.S.	4	10	30
Total	96	157	213

Table 5.2 Summary Information on the Correlations Used in Ω [40]

Markets	N	Mean	Max	Min
China-US	20	0.1133	0.4028	-0.1008
China-Hong Kong	32	0.0858	0.3777	-0.1848
Hong Kong-US	80	0.6088	0.8792	0.0000

[40] We employ 126 days return in estimation period and calculate their dual-listing return correlations. We assume constant correlations across 147 days return for each dual-listing and apply estimation period correlations to adjust abnormal return correlations in test period.

Table 5.3 Stock Price Disparity Between Multi-listing Pairs
(Mean Absolute Percentage Deviation)[41]

A & H multi-listings		H & US multi-listings		A & US multi-listings	
Sinopec	0.4551	China Mobile	0.0206	China Ptl.& Chm.	0.4541
Huaneng Power Intl.	0.3995	China Ptl.& Chm.	0.0228	Yanzhou Coal mining	0.4080
Yanzhou Coal mining	0.4099	Lenovo GP.	0.0202	China Life Insurance	0.1239
China Life Insurance	0.1232	PetroChina	0.0224	PetroChina	0.4711
Aluminum Corp. of China	0.5081	China Netcom GP.	0.0222		
China Nonferrous Metals	0.9854	China Telecom SR.	0.0232		
Angang Steel	0.1931	CNOOC	0.0248		
PetroChina	0.4719	China Res.entrep.	0.0778		
		Yuexiu Property	0.9121		

A & H multi-listings		**H & US multi-listings**		**A & US multi-listings**
		China Unic.	0.0247	
		Yanzhou Coal mining	0.0264	
		China Life Insurance	0.0225	
Mean	*0.4732*	*0.0480*		*0.4089*
Median	*0.4551*	*0.0228*		*0.4541*

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

Table 5.4 Daily Results Comparison

DAY	Mainland-listing (64)		liquid-listing (157)		Multi-listing (213)		
	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{GLS-2}$
-10	0.0011 (0.39)	0.0009 (0.40)	0.0026 (0.95)	0.0021 (1.31)	0.0026 (1.19)	0.0018 (1.35)	0.0022 (1.53)
-9	0.0037 (1.35)	0.0022 (0.99)	0.0025 (0.93)	0.0018 (1.16)	0.0026 (1.15)	0.0021 (1.54)	0.0023 (1.59)
-8	0.0018 (0.64)	0.0020 (0.91)	-0.0003 (-0.10)	0.0001 (0.04)	-0.0004 (-0.18)	-0.0003 (-0.23)	-0.0005 (-0.34)
-7	0.0001 (0.02)	-0.0002 (-0.11)	-0.0031 (-1.15)	-0.0012 (-0.76)	-0.0033 (-1.47)	-0.0015 (-1.07)	-0.0001 (-0.08)
-6	0.0005 (0.17)	-0.0010 (-0.44)	-0.0017 (-0.61)	-0.0020 (-1.31)	-0.0012 (-0.54)	-0.0023 (-1.71)	-0.0026 (-1.81)
-5	0.0040 (1.45)	0.0014 (0.64)	0.0061** (2.22)	0.0007 (0.43)	0.0051** (2.28)	0.0006 (0.43)	0.0009 (0.66)
-4	0.0009 (0.32)	0.0030 (1.37)	-0.0023 (-0.85)	0.0022 (1.39)	-0.0015 (-0.65)	0.0013 (0.95)	0.0016 (1.12)
-3	-0.0003 (-0.11)	-0.0001 (-0.07)	0.0000 (0.00)	0.0011 (0.68)	-0.0005 (-0.24)	0.0004 (0.26)	0.0010 (0.66)
-2	0.0016 (0.59)	0.0014 (0.64)	-0.0022 (-0.81)	-0.0006 (-0.40)	-0.0028 (-1.24)	-0.0011 (-0.78)	-0.0012 (-0.80)
-1	0.0087*** (3.18)	0.0062*** (2.83)	0.0036 (1.32)	0.0030 (1.90)	0.0033 (1.49)	0.0022 (1.61)	0.0029** (2.01)
0	0.0003 (0.11)	0.0019 (0.86)	0.0044 (1.61)	0.0017 (1.05)	0.0044** (1.99)	0.0012 (0.91)	0.0011 (0.77)
1	-0.0010 (-0.35)	-0.0019 (-0.85)	0.0040 (1.48)	0.0019 (1.23)	0.0054** (2.43)	0.0031** (2.28)	0.0025 (1.72)
2	-0.0060** (-2.20)	-0.0050** (-2.29)	-0.0059** (-2.17)	-0.0010 (-0.64)	-0.0052** (-2.35)	-0.0013 (-0.96)	-0.0012 (-0.83)
3	0.0002 (0.07)	0.0005 (0.22)	-0.0056** (-2.05)	-0.0021 (-1.35)	-0.0047** (-2.13)	-0.0019 (-1.42)	-0.0024 (-1.65)
4	-0.0045 (-1.64)	-0.0031 (-1.41)	-0.0024 (-0.86)	-0.0016 (-1.04)	-0.0010 (-0.45)	-0.0008 (-0.60)	-0.0011 (-0.78)
5	0.0038 (1.37)	0.0020 (0.94)	0.0014 (0.50)	0.0014 (0.91)	0.0018 (0.83)	0.0018 (1.33)	0.0015 (1.06)

DAY	Mainland-listing (64)		liquid-listing (157)		Multi-listing (213)		
	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{GLS-2}$
6	-0.0010 (-0.36)	0.0006 (0.28	-0.0017 (-0.63)	-0.0012 (-0.77)	0.0000 (-0.01)	-0.0003 (-0.22)	-0.0012 (-0.83)
7	0.0029 (1.06)	0.0019 (0.86)	0.0045 (1.65)	0.0008 (0.48)	0.0034 (1.53)	0.0005 (0.36)	0.0010 (0.69)
8	0.0010 (0.38)	0.0026 (1.21)	0.0005 (0.18)	0.0013 (0.86)	0.0010 (0.43)	0.0012 (0.87)	0.0009 (0.62)
9	-0.0023 (-0.85)	-0.0034 (1.56)	-0.0006 (-0.23)	-0.0015 (-0.98)	-0.0004 (-0.19)	-0.0012 (-0.91)	-0.0011 (-0.80)
10	-0.0034 (-1.24)	-0.0039 (-1.77)	-0.0031 (-1.13)	-0.0018 (-1.15)	-0.0028 (-1.25)	-0.0016 (-1.19)	-0.0014 (-0.99)

Note: $\hat{\beta}_{OLS}$ refers to estimations from the OLS procedure; $\hat{\beta}_{GLS-1}$ refers to estimations from the GLS procedure that only corrects for heteroscedasticity; $\hat{\beta}_{GLS-2}$ refers to estimations of the GLS procedure that corrects for both heteroscedasticity and cross-sectional dependence. Figures in brackets are Z statistics of point estimates.

Table 5.5 Interval Results Comparison

Interval	Mainland-listing (64)		Single-listing (157)		Multi-listing (213)		
	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{OLS}$	$\hat{\beta}_{GLS-1}$	$\hat{\beta}_{GLS-2}$
(-10,-6)	0.0071	0.0008	0.0000	0.0001	0.0003	0.0000	0.0003
	(1.15)	(0.78)	(0.00)	(0.20)	(0.06)	(0.06)	(0.40)
(-5,-1)	0.0149**	0.0024**	0.0051	0.0012	0.0036	0.0007	0.0011
	(2.43)	(2.42)	(0.84)	(1.79)	(0.73)	(1.11)	(1.64)
(-1,1)	0.0081	0.0021	0.0120**	0.0022**	0.0131***	0.0022***	0.0022***
	(1.70)	(1.64)	(2.54)	(2.41)	(3.41)	(2.77)	(2.61)
(1,5)	-0.0076	-0.0015	-0.0085	-0.0003	-0.0037	0.0002	-0.0001
	(-1.24)	(-1.52)	(-1.39)	(-0.40)	(-0.75)	(0.28)	(-0.21)
(6,10)	-0.0028	-0.0004	-0.0005	-0.0005	0.0012	-0.0003	-0.0004
	(-0.45)	(-0.44)	(-0.08)	(-0.69)	(-0.23)	(-0.49)	(-0.59)
(-2,2)	0.0037	0.0005	0.0039	0.001	0.0052	0.0008	0.0008
	(0.59)	(0.53)	(0.64)	(1.40)	(1.04)	(1.36)	(1.29)
(-3,3)	0.0035	0.0004	-0.0017	0.0006	-0.0001	0.0004	0.0004
	(0.49)	(0.50)	(-0.24)	(0.93)	(-0.02)	(0.71)	(0.72)
(-5,5)	0.0076	0.0006	0.001	0.0006	0.0043	0.0005	0.0005
	(0.84)	(0.87)	(0.11)	(1.25)	(0.59)	(1.21)	(1.19)
(-10,10)	0.0119	0.0004	0.0006	0.0002	0.0058	0.0002	0.0002
	(0.95)	(0.79)	(0.05)	(0.67)	(0.57)	(0.61)	(0.77)

Note: $\hat{\beta}_{OLS}$ refers to estimations from the OLS procedure; $\hat{\beta}_{GLS-1}$ refers to estimations from the GLS procedure that only corrects for heteroscedasticity; $\hat{\beta}_{GLS-2}$ refers to estimations of the GLS procedure that corrects for both heteroscedasticity and cross-sectional dependence. Figures in brackets are Z statistics of point estimates.

Figures

Figure 3.1 Acquiring Firm's Demand and Supply of OMA Projects

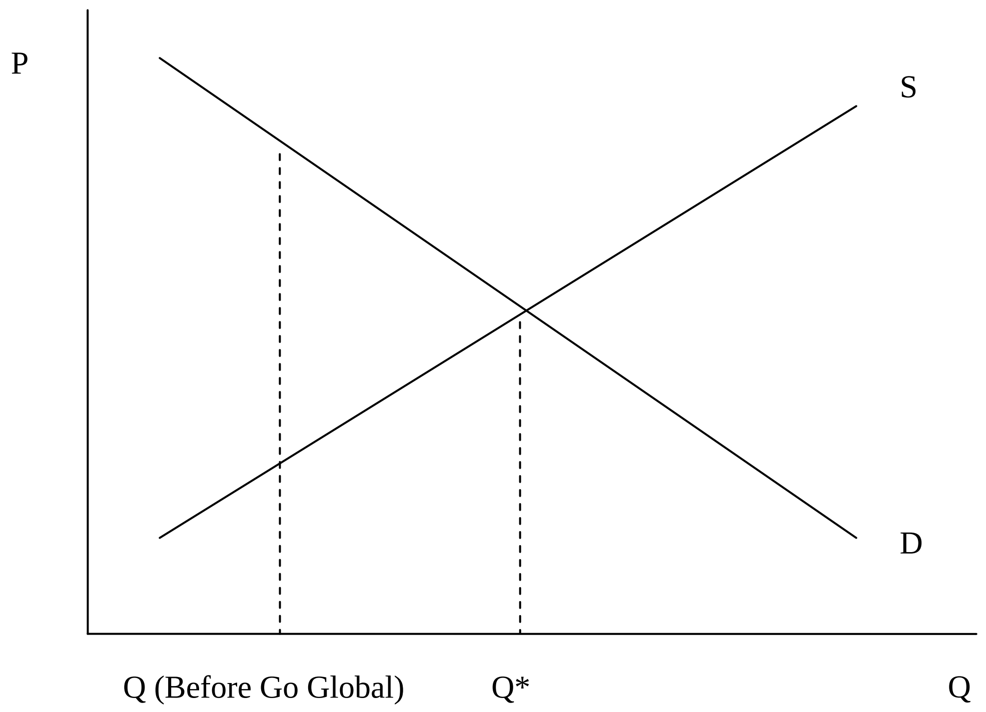
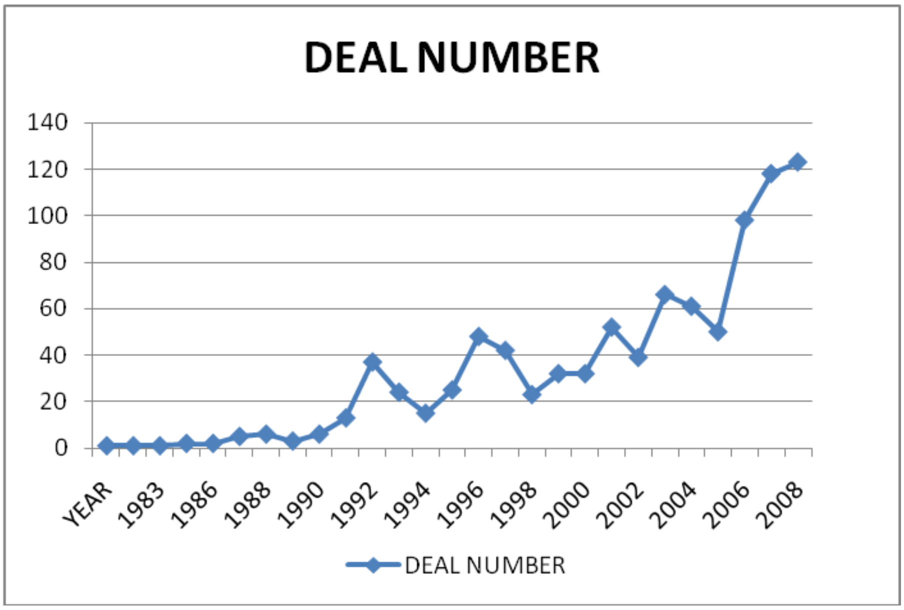
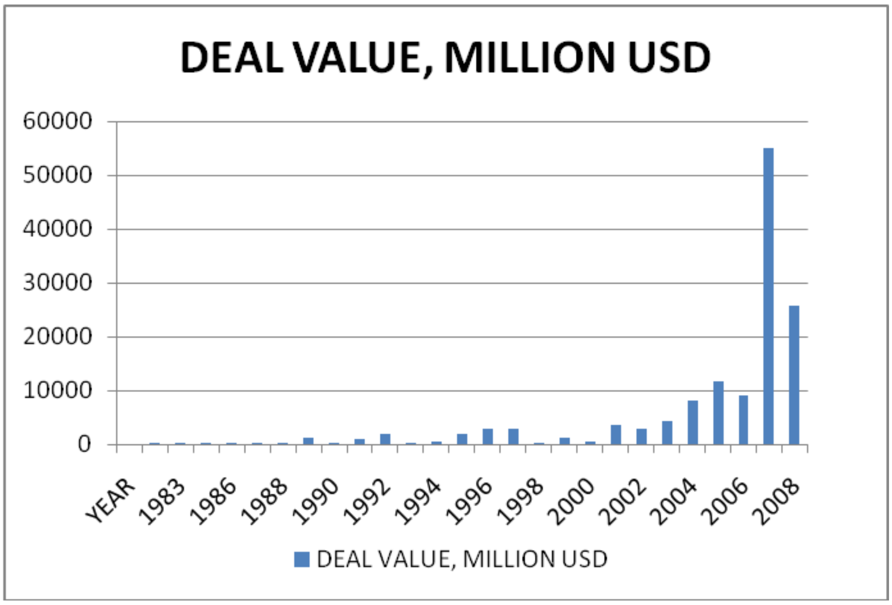


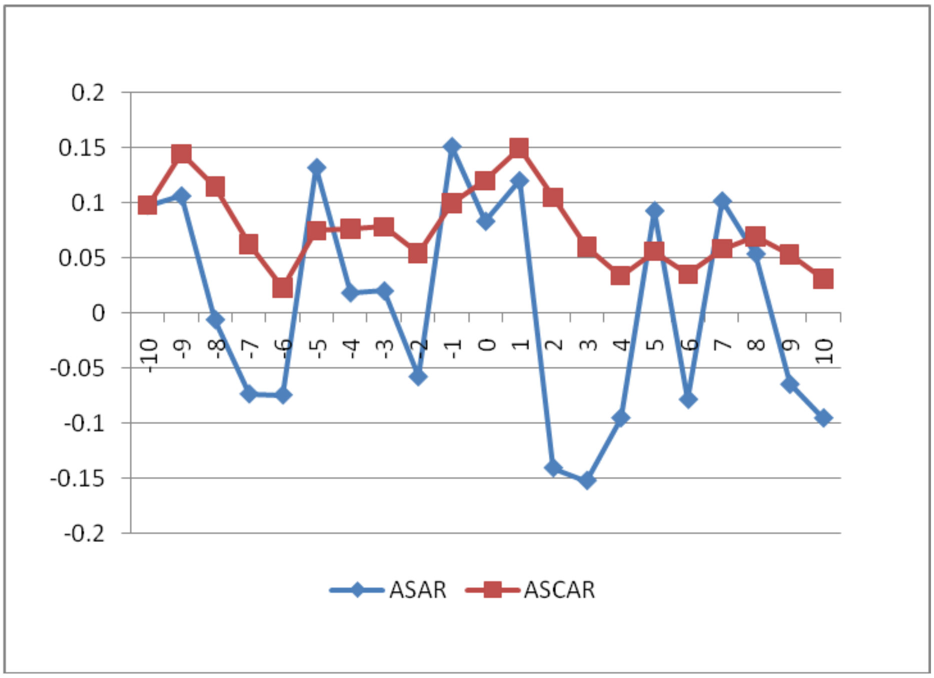
Figure 3.2 Chinese OMAs: 1982-2009





Source: SDC Platinum M&A database

Figure 3.3 Stock Market Performance of Chinese OMAs: 1994-2009



Appendices

Appendix 1

A.1.1. Proof of Z statistics in Equations (8) and (10)in Chapter Three

In this section, we derive the formulae for the Z-statistics in Equations (8) and (10) in the text. Let AR_{it} represent abnormal returns for security i at time t. Assume abnormal returns are independent and normally distributed: $AR_{it} \sim N(0, \sigma_{it})$, where σ_{it} is the standard deviation of abnormal returns during the test period.

If we knew σ_{it}, then $\dfrac{AR_{it}}{\sigma_{it}}$ would be independent and standard normal distributed: $\dfrac{AR_{it}}{\sigma_{it}} \sim N(0,1)$. We could then compare $\dfrac{AR_{it}}{\sigma_{it}}, i = 1,...,N; t = 1,...,T;$ with the critical Z value to test whether $\dfrac{AR_{it}}{\sigma_{it}}$ is significantly different from 0.

In practise, we wouldn't test the significance of each $\dfrac{AR_{it}}{\sigma_{it}}$ because there are too many of them and they are likely to give conflicting results. Therefore, we prefer to test the sum, or the mean, of these $\dfrac{AR_{it}}{\sigma_{it}}$s. We first derive the variance for the sum of abnormal returns on a given test day t across firms, $\sum_{i=1}^{N} \dfrac{AR_{it}}{\sigma_{it}}$.

Note that the $\text{var}(\sum_{i=1}^{N} \dfrac{AR_{it}}{\sigma_{it}}) \equiv \text{var}(\dfrac{AR_{1t}}{\sigma_{1t}} + \dfrac{AR_{2t}}{\sigma_{2t}} + ... + \dfrac{AR_{Nt}}{\sigma_{Nt}})$. If, as assumed, the $\dfrac{AR_{it}}{\sigma_{it}}$ are distributed independently, then the variance of the sum equals the sum of the individual variances, $\text{var}(\dfrac{AR_{1t}}{\sigma_{1t}} + \dfrac{AR_{2t}}{\sigma_{2t}} + ... + \dfrac{AR_{Nt}}{\sigma_{Nt}}) = \text{var}(\dfrac{AR_{1t}}{\sigma_{1t}}) + \text{var}(\dfrac{AR_{2t}}{\sigma_{12t}}) + \cdots \text{var}(\dfrac{AR_{Nt}}{\sigma_{Nt}})$. However, since each of the *ARs* is standardized, the variances of the individual $\frac{AR_{it}}{\sigma_{it}}$ terms are each equal to 1. Thus, $\operatorname{var}(\sum_{i=1}^{N}\frac{AR_{it}}{\sigma_{it}}) = 1+1+\cdots 1 = N.$; and the corresponding standard deviation is $\sqrt{N}$. Note further that if the individual $\frac{AR_{it}}{\sigma_{it}}$ terms are normally distributed, then the sum of these terms will also be normally distributed.

If we divide the sum of the abnormal returns for a given test day by its standard deviation, call it

(A.1) $$Z_t = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\frac{AR_{it}}{\sigma_{it}} \quad ,$$

then Z will be normally distributed with variance equal to 1, $Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\frac{AR_i}{\sigma_i} \sim N(0,1)$.

The previous analysis is easily extended to the case when cumulative abnormal returns are summed over the interval (T_1, T_1+1,…,T_2).

In this case

$$\operatorname{var}(\sum_{t=T_1}^{T_2}\sum_{i=1}^{N}\frac{AR_{it}}{\sigma_{it}}) = (T_2 - T_1 + 1)\cdot N.$$

The compounding standard deviation is

$$\sqrt{T_2 - T_1 + 1}\cdot\sqrt{N}.$$

Now define that

（A．2） $$Z = \frac{1}{\sqrt{T_2 - T_1 + 1}\cdot\sqrt{N}}\sum_{t=T_1}^{T_2}\sum_{i=1}^{N}\frac{AR_{it}}{\sigma_{it}}.$$

It follows that

$$Z = \frac{1}{\sqrt{T_2 - T_1 + 1}\cdot\sqrt{N}}\sum_{t=T_1}^{T_2}\sum_{i=1}^{N}\frac{AR_{it}}{\sigma_{it}} \sim N(0,1).$$

Many researchers find it convenient to work with the mean of the sum of $\frac{AR_{it}}{\sigma_{it}}$ (ASAR).

Consider first the single period are defined

(A.3) $SAR_{it} = AR_{jt} / \sigma_{jt}$

Then

(A.4) $$ASAR_t = \frac{\sum_{i=1}^{N} SAR_{it}}{N}$$

$$\text{var}(ASAR_t) = \frac{1}{N^2}\text{var}(\sum_{i=1}^{N} SAR_{it}) = \frac{1}{N^2} \cdot N = \frac{1}{N}.$$

The associated standard deviation is $\frac{1}{\sqrt{N}}$.

Define

(A.5) $$Z = \frac{ASAR_t}{(1/\sqrt{N})} = \sqrt{N} \cdot ASAR_t$$

For reasons given earlier,

$$Z = \sqrt{N} ASAR_t \sim N(0,1).$$

It is straightforward to show that the Z in (A.5) is identical to the Z in (A.1)

Similarly, researchers sometimes prefer to work with the average of the standardized cumulative abnormal returns (ASCAR).

(A.6) $$ASCAR_{T_1,T_2} = \frac{1}{N}\sum_{t=T_1}^{T_2}\sum_{i=1}^{N} SAR_{it}$$

$$\text{var}(ASCAR_{T_1,T_2}) = \frac{1}{N^2}\text{var}(\sum_{t=T_1}^{T_2}\sum_{i=1}^{N} SAR_{it}) = \frac{1}{N^2}(T_2 - T_1 + 1) \cdot N = \frac{1}{N}(T_2 - T_1 + 1).$$

The associated standard deviation is $\frac{1}{\sqrt{N}}\sqrt{T_2 - T_1 + 1}.$

Define

(A.7) $$Z = \frac{ASCAR_{T_1,T_2}}{1/\sqrt{N} \cdot \sqrt{T_2 - T_1 + 1}} = \frac{\sqrt{N}}{\sqrt{T_2 - T_1 + 1}} \cdot ASCAR_{T_1,T_2}$$

It follows that

$$Z = \frac{\sqrt{N}}{\sqrt{T_2 - T_1 + 1}}, ASCAR_{T_1,T_2} \sim N(0,1)$$

Further, the Z in (A.7) is easily shown to be identical to the Z in (A.2).

Equations (A.1),(A.2),(A.5) and (A.7) appear frequently in the literature, albeit with different notation.

For example, equation (9) in Mikkelson and Partch (1986) reports the Z test statistic as

(A.8) $$Z = \sqrt{N}(AISPE_{T1,T2}),$$

where $AISPE_{T1,T2}$ stands for "average interval standardized predicted error" in time period T1 to T2 and is defined by

(A.9) $$AISPE_{T_1,T_2} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=T_{1i}}^{T_{2i}} SPE_{it} / \sqrt{T_2 - T_1 + 1}.$$

However $SPE_{jt} = SAR_{jt}$;

So $$AISPE_{T_1T_2} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=T_1}^{T_2} \frac{SAR_{it}}{\sqrt{T_2 - T_1 + 1}}.$$

From equation (A.6),

(A.10) $$AISPE_{T_1,T_2} = \frac{1}{\sqrt{T_2 - T_1 + 1}} \cdot ASCAR_{T_1,T_2}.$$

Substituting (A.10) into (A.8) gives

(A.11) $$Z = \frac{\sqrt{N}}{\sqrt{T_2 - T_1 + 1}} \cdot ASCAR_{T_1,T_2}.$$

which is identical to the Z in (A.7).

Because the sample is standard normally distributed, we use the Z-test to test the null hypothesis that the respective mean equal to 0. Testing proceeds by comparing the sample value of Z with the appropriate critical Z value.

A.1.2. Estimating the Standard Deviation of Abnormal Returns for Firm *i*.

In practise, we don't know σ_{it}. One approach is to assume $\sigma_{it} = \sigma$ for all i and t.

To estimate σ, we calculate abnormal returns for each security and time period. σ is estimated by the sample standard deviation for all abnormal returns during the estimation period.

We define abnormal returns, AR$_{it}$ are

(A. 12) $AR_{it} = [R_{it} - E(R_{it})]$.

We estimate expected returns for security *i* at time *t*, E(R$_{it}$), using the market model.

(A. 13) $\hat{R}_{it} = E(R_{it}) = \hat{\alpha} + \hat{\beta}R_{mt}$.

When $\hat{\alpha}_i$ and $\hat{\beta}_i$ come from estimating the model

(A.14) $R_{is} = \alpha_i + \beta_i R_{ms} + \varepsilon_{is}$

Using observations from the estimation period. Suppose there are S observations for each of N securities, then

(A.15) $$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{N}\sum_{s=1}^{S}[R_{it} - \hat{R}_{it}]^2}{NS-2}} = \sqrt{\frac{\sum_{i=1}^{N}\sum_{s=1}^{S}e_{it}{}^2}{NS-2}}.$$

When e_{it} is the residual from the regression of (A.14).

Substituting AR$_{it}$ and $\hat{\sigma}_{it} = \hat{\sigma}$ into (A.1), (A.2), (A.5) and (A.7) produces the appropriate sample statistic. Strictly speaking, this sample statistic is distributed *t*. however, the standard normal distribution is a good approximation when (NS-2)>30.

A less restrictive approach for estimating σ_{it} allows $\hat{\sigma}_{\text{it}}$ to be different for *i* and *t*. Patell (1976) assumes, each security has a different variance. Let s_i^2 be the variance of the residuals for security *i* during the estimation period,

(A.16) $s_i^2 = \dfrac{\sum_{s=1}^{S} \hat{e}_{is}^{\,2}}{S-2}$ (also see Beaver (1968)).

Patell shows that the standard deviation for the abnormal returns for security *i* at time *t* (in the test period) can be estimated by

(A.17) $\hat{\sigma}_{\text{it}} = s_i \times \sqrt{c_{it}}$

where

(A.18) $c_{it} = 1 + \dfrac{1}{S} + \dfrac{(R_{mt} - \bar{R}_m)^2}{\sum_{s=1}^{S} (R_{ms} - \bar{R}_m)^2}$

(A.19) $\bar{R}_m = \dfrac{1}{S} \sum_{s=1}^{S} R_{ms}$

S equals number of days in estimation period, and c_{it} reflects the increase in variance due to prediction outside the estimation period.

We next show how this formula is derived. Abnormal returns as an defined in (A.12) and (A.13) as

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

where $\hat{R}_{it}$ is the predicted value at time t in the test period based on the estimation of $R_{is} = \alpha_i + \beta_i R_{ms} + \varepsilon_{is}$. for the estimation period.

Thus

(A.20) $\text{var}(AR \mid R_{mt}) = \text{var}(R_{it} \mid R_{mt}) + \text{var}(\hat{R}_{it} \mid R_{mt}) - 2\,\text{cov}(R_{it}\hat{R}_{it} \mid R_{mt}).$

We assume that R_{it} and $\hat{R}_{it}$ are independent because the $\hat{\alpha}_i$ and $\hat{\beta}_i$ used to calculate $\hat{R}_{it}$ come from the estimation period, not the test period, therefore,

(A.21) $\operatorname{cov}(R_{it}\hat{R}_{it} \mid R_{mt}) = 0.$

Further

(A.22) $\operatorname{var}(R_{it} \mid R_{mt}) = \operatorname{var}(\alpha_i + \beta_i R_{mt} + \varepsilon_{it} \mid R_{mt}) = \operatorname{var}(\varepsilon_{it}) = \sigma_{it}{}^2,$

and

(A.23) $$\begin{aligned}&\operatorname{var}(\hat{R}_{it} \mid R_{mt}) = \operatorname{var}(\hat{\alpha}_i + \hat{\beta}_i R_{mt} \mid R_{mt})\\ &= \operatorname{var}(\hat{\alpha}_i) + \operatorname{var}(\hat{\beta}_i R_{mt} \mid R_{mt}) + 2\operatorname{cov}(\hat{\alpha}_i \hat{\beta}_i R_{mt} \mid R_{mt}).\end{aligned}$$

It can be shown that $\hat{\alpha}_i$ and $\hat{\beta}_i$ are independent, thus $\operatorname{cov}(\hat{\alpha}_i\hat{\beta}_i R_{mt} \mid R_{mt}) = 0;$

It can also be shown that $\operatorname{var}(\hat{\alpha}_i) = \dfrac{\sigma_i{}^2}{S}$ And $\operatorname{var}(\hat{\beta}_i R_{mt} \mid R_{mt}) = \sigma_i{}^2 \times \dfrac{(R_{mt} - \bar{R}_m)^2}{\sum_{s=1}^{S}(R_{ms} - \bar{R}_m)^2}.$

Substituting the above into (A.23) yields

(A.24) $\operatorname{var}(\hat{R}_{it} \mid R_{mt}) = \operatorname{var}(\hat{\alpha}_i) + \operatorname{var}(\hat{\beta}_i R_{mt} \mid R_{mt}) + 2\operatorname{cov}(\hat{\alpha}_i \hat{\beta}_i R_{mt})$

$$= \frac{\sigma_i{}^2}{S} + \sigma_i{}^2\left(\frac{(R_{mt} - \bar{R}_m)^2}{\sum_{s=1}^{S}(R_{ms} - \bar{R}_m)^2}\right) + 0$$

where

S is the number of observations in estimation period and $\bar{R}_m = \dfrac{1}{S}\sum_{s=1}^{S} R_{ms}$

Substituting (A.24), (A.22) and (A.21) into (A.20) yields

(A.25) $\operatorname{var}(AR_{it} \mid R_{mt}) = \sigma_i{}^2 + \dfrac{\sigma_{it}{}^2}{S} + \sigma_i{}^2\left(\dfrac{(R_{mt} - \bar{R}_m)^2}{\sum_{s=1}^{S}(R_{ms} - \bar{R}_m)^2}\right) = \sigma_i{}^2\left(1 + \dfrac{1}{S} + \dfrac{(R_{mt} - \bar{R})^2}{\sum_{s=1}^{S}(R_{ms} - \bar{R}_m)^2}\right)$

Finally,

(A.26) $$Stddev(AR_{it} \mid R_{mt}) = \hat{\sigma}_{it} = \sigma_i \sqrt{1 + \frac{1}{S} + \frac{(R_{mt} - \bar{R}_m)^2}{\sum_{s=1}^{S} (R_{ms} - \bar{R}_m)^2}}.$$

See (Brown, 1985; Doukas & Travlos, 1988; Dunne & Ndubizu, 1995; Mikkelson & Partch, 1986; Patell, 1976)

Appendix 2. Matlab Coding in Chapter Three

In this section, we report the Matlab code edited for calculating daily and interval abnormal returns of Chinese OMAs with event study methodology in Chapter Three.

```
%% INPUT: RC1,RM1,testRC1,testRM1,LIST
RC=RC1';  % return matrix for securities in estimation period;
RM=RM1';  % return matrix for market indices in estimation period;
testRC=testRC1';  % return matrix for securities in test period;
testRM=testRM1';  % return matrix for market indices in test period;

%% FOR DAILY Z VALUE AND P VALUE OF ABNORMAL RETURNS
A=size(RC);
L=A(1); % number of days in estimation period
rbarm=sum(RM)/L; % average market return in estimation period
for i=1:A(2); % i refers to columns of the matrix (number of securities)
   B(:,i) =sum((RM(:,i)-rbarm(:,i)).^2);
   C(:,i)=(testRM(:,i)-rbarm(:,i)).^2;
   D(:,i)=1+1/L+C(:,i)/B(:,i);
   [b(:,i),bint,r,rint,stats] = regress(RC(:,i),[ones(L,1),RM(:,i)]); % regression function with market model
   s2(:,i)=stats(:,4);    % error variance for idividual security from market model
   sjt(:,i)=sqrt(s2(:,i).*D(:,i)); % square root of firm j's estimated forecast variance
   er=testRM.*b(2,i)+b(1,i);  % expected returns in test period
   ar(:,i)=testRC(:,i)-er(:,i);  % abnormal return in test period
   AAR=mean(ar')'; % average abnormal returns in test period
   SAR=(ar./sjt)';   % standardized abnormal returns
   SAR1=SAR';  %transpost standardized abnormal returns
   ASAR=(1/A(2))*sum((ar./sjt)')';  % average standardized abnormal returns in test period
   Z1=(A(2)^0.5)*ASAR;   % Z value of daily average standardized abnormal returns
   p1=2*(1-normcdf(abs(Z1)));  % p value of daily average abnormal returns
end

%% FOR INTERVAL Z & p
for i=1:A(2)
       car1(:,i)=sum(ar(1:6,i));
       %  vector,cumulated abnormal return of interval (-10,-5);
       car2(:,i)=sum(ar(1:10,i));
       %  vector,cumulated abnormal return of interval (-10,-1);
       car3(:,i)=sum(ar(6:10,i));
       %  vector,cumulated abnormal return of interval (-5,-1);
       car4(:,i)=sum(ar(10:12,i));
       %  vector,cumulated abnormal return of interval (-1,1);
       car5(:,i)=sum(ar(12:16,i));
       %  vector,cumulated abnormal return of interval (1,5);
       car6(:,i)=sum(ar(16:21,i));
       %  vector,cumulated abnormal return of interval (5,10);
       car7(:,i)=sum(ar(12:21,i));
       %  vector,cumulated abnormal return of interval (1,10);
       car8(:,i)=sum(ar(6:16,i));
       %  vector,cumulated abnormal return of interval (-5,5);
       car9(:,i)=sum(ar(1:21,i));
       %  vector,cumulated abnormal return of interval (-10,10);
       car10(:,i)=sum(ar(9:13,i));
       %  vector,cumulated abnormal return of interval (-2,2);
       car11(:,i)=sum(ar(8:14,i));
       %  vector,cumulated abnormal return of interval (-3,3);
```

```
ACAR=[mean(car1');mean(car2');mean(car3');mean(car4');mean(car5');mean(car6');mean(car7');mean(car8');me
an(car9');mean(car10');mean(car11')];
   % average cumulated abnormal return of intervals

SCAR(:,i)=[sum(SAR(1:6,i));sum(SAR(1:10,i));sum(SAR(6:10,i));sum(SAR(10:12,i));sum(SAR(12:16,i));sum(
SAR(16:21,i));sum(SAR(12:21,i));sum(SAR(6:16,i));sum(SAR(1:21,i));sum(SAR(9:13,i));sum(SAR(8:14,i))]';
end
%  FOR INTERVAL P MATRIX AND ADJUSTED Z VALUE AND P VALUE
   C=[6,10,5,3,5,6,10,11,21,5,7];
%  length (days) of 11 intervals defined above.
   ASCAR=sum(SCAR')./(A(2).*sqrt(C));
% average standardized cumulative abnormal returns
   Z2=sum(SCAR')./sqrt(A(2).*C);
% Z value of interval standardized abnormal returns
   p2=2*(1-normcdf(abs(Z2)));
% p value of interval standardized abnormal returns

%% performance
DATRADAILY=[AAR,ASAR,Z1,p1]; % daily results
INTRAINTERVAL=[ACAR,ASCAR’,Z2’,p2’]; % interval results
```

Appendix 3 Matlab Coding in Chapter Five

A.3.1. Matlab Coding for OLS Estimator

```
%% INPUT: RC1,RM1,testRC1,testRM1,LIST
RC=RC1';  % return matrix for securities in estimation period;
RM=RM1';  % return matrix for market indices in estimation period;
testRC=testRC1'; % return matrix for securities in test period;
testRM=testRM1';  % return matrix for market indices in test period;
% LIST is  multilist vector.
%% FOR DAILY Z VALUE AND P VALUE OF ABNORMAL RETURNS
A=size(RC);   L=A(1);   % A(1) refers to number of days in estimation period, A(2) refers to number of
securities.
rbarm=sum(RM)/L;
for i=1:A(2); % i refers to columns of the matrix (number of securities)
   B(:,i) =sum((RM(:,i)-rbarm(:,i)).^2);
   C(:,i)=(testRM(:,i)-rbarm(:,i)).^2;
   D(:,i)=1+1/L+C(:,i)/B(:,i);
   [b(:,i),bint,r,rint,stats] = regress(RC(:,i),[ones(L,1),RM(:,i)]); % regression function with market model
   s2(:,i)=stats(:,4);    % error variance for idividual security from market model(squared one)
   er=testRM.*b(2,i)+b(1,i);
   ar(:,i)=testRC(:,i)-er(:,i);  % abnormal return matrix
   AAR=mean(ar')';   %   mean abnorma returns on days
   sjt=sqrt((sum(s2)/(A(2)-1))); % segma of idividual securities
   SAR=(ar./sjt);   % standardized abnormal returns 21x213
   SAR1=SAR';  % standardized abnormal returns 213x21
   ASAR=(1/A(2))*sum((ar./sjt)')';  % standardized abnormal returns for each day in test period
end
%% FOR P MATRIX AND ADJUSTED Z VALUE AND P VALUE
for i=1:21;
   Z=sqrt(A(2))*ASAR;
   p=2*(1-normcdf(abs(Z)));
end
% FOR CUMULATIVE Z AND p VALUE
ASCAR=[sum(ASAR(1:5))/sqrt(5),sum(ASAR(6:10))/sqrt(5),sum(ASAR(10:12))/sqrt(3),sum(ASAR(12:16))/s
qrt(5),sum(ASAR(17:21))/sqrt(5),sum(ASAR(9:13))/sqrt(5),sum(ASAR(8:14))/sqrt(7),sum(ASAR(6:16))/sqrt(1
1),sum(ASAR(1:21))/sqrt(21)]';
for i=1:A(2),t=1:21;
   car1(:,i)=sum(ar(1:5,i)); %vector,cumulated abnormal return of interval (-10,-6);
   car2(:,i)=sum(ar(6:10,i)); %vector,cumulated abnormal return of interval (-5,-1);
   car3(:,i)=sum(ar(10:12,i)); %vector,cumulated abnormal return of interval (-1,1);
   car4(:,i)=sum(ar(12:16,i)); %vector,cumulated abnormal return of interval (1,5);
   car5(:,i)=sum(ar(17:21,i)); %vector,cumulated abnormal return of interval (6,10);
   car6(:,i)=sum(ar(9:13,i)); %vector,cumulated abnormal return of interval (-2,2);
   car7(:,i)=sum(ar(8:14,i)); %vector,cumulated abnormal return of interval (-3,3);
   car8(:,i)=sum(ar(6:16,i)); %vector,cumulated abnormal return of interval (-5,5);
   car9(:,i)=sum(ar(1:21,i)); %vector,cumulated abnormal return of interval (-10,10);

ACAR=[mean(car1');mean(car2');mean(car3');mean(car4');mean(car5');mean(car6');mean(car7');mean(car8');me
an(car9')]; % mean cumulated abnormal returns
end
%% FOR INTERVAL P MATRIX AND ADJUSTED Z VALUE AND P VALUE
for i=1:21
   Z4=sqrt(A(2))*ASCAR;
   p4=2*(1-normcdf(abs(Z4)));
end
%% performance
```

```
DAILY=[AAR';Z'];
DAILY=DAILY(:);  %Adjusted results for daily ASAR, Z test and p value
INTERVAL=[ACAR';Z4'];
INTERVAL=INTERVAL(:);   %Adjusted results for interval ASCAR, Z test and p value
```

A.3.2. Matlab Coding for GLS-1 Estimator

```
%% INPUT: RC1,RM1,testRC1,testRM1,LIST
RC=RC1';  % return matrix for securities in estimation period;
RM=RM1';  % return matrix for market indices in estimation period;
testRC=testRC1'; % return matrix for securities in test period;
testRM=testRM1';  % return matrix for market indices in test period;
% LIST is  multilist vector.
%% For studentized STAR
A=size(RC); % A(1) refers to number of days in estimation period, A(2) refers to number of securities.
OMEGA=eye(A(2));  %% correlation matrix with only multi-listing coefficients.
P= chol(inv(OMEGA));  % omega inverse matrix 213x213
%% FOR DAILY Z VALUE AND P VALUE OF ABNORMAL RETURNS
L=A(1);
rbarm=sum(RM)/L;
for i=1:A(2); % i refers to columns of the matrix (number of securities)
    B(:,i) =sum((RM(:,i)-rbarm(:,i)).^2);
    C(:,i)=(testRM(:,i)-rbarm(:,i)).^2;
    D(:,i)=1+1/L+C(:,i)/B(:,i);
    [b(:,i),bint,r,rint,stats] = regress(RC(:,i),[ones(L,1),RM(:,i)]); % regression function with market model
    s2(:,i)=stats(:,4);    % error variance for idividual security from market model(squared one)
    er=testRM.*b(2,i)+b(1,i);
    ar(:,i)=testRC(:,i)-er(:,i);  % abnormal return matrix
    AAR=mean(ar')';   %   mean abnorma returns on days
    sjt(:,i)=(s2(:,i).*D(:,i)).^0.5; % segma of idividual securities
    SAR=(ar./sjt);  % standardized abnormal returns 21x213
    SAR1=SAR';  % standardized abnormal returns 213x21
    ASAR=(1/A(2))*sum((ar./sjt)')';  % standardized abnormal returns for each day in test period
end
xtidea=ones(A(2),21)./sjt';  % standardized ones matrix 213x21
E=xtidea';   % standardized ones matrix (21x213)
%% FOR P MATRIX AND ADJUSTED Z VALUE AND P VALUE
for i=1:21;

ASCAR=[sum(ASAR(1:5))/sqrt(5),sum(ASAR(6:10))/sqrt(5),sum(ASAR(10:12))/sqrt(3),sum(ASAR(12:16))/s
qrt(5),sum(ASAR(17:21))/sqrt(5),sum(ASAR(9:13))/sqrt(5),sum(ASAR(8:14))/sqrt(7),sum(ASAR(6:16))/sqrt(1
1),sum(ASAR(1:21))/sqrt(21)]';
   NU1(:,i)=inv(E(i,:)*xtidea(:,i));   % first part of numerater
   NU2(:,i)=E(i,:)*SAR1(:,i);    % second part of numerater
   DE(:,i)=sqrt(inv(E(i,:)*xtidea(:,i)));     % denominator
   SDE(:,i)=E(i,:)*xtidea(:,i);
   betah(:,i)=(NU1(:,i)*NU2(:,i));
   Z(:,i)=(NU1(:,i)*NU2(:,i))/DE(:,i);   %Z value of daily betahat
   p=2*(1-normcdf(abs(Z)));   %p value of daily AAR
end
% FOR CUMULATIVE Z AND p VALUE
for i=1:A(2),t=1:21;
    car1(:,i)=sum(ar(1:5,i)); %vector,cumulated abnormal return of interval (-10,-6);
    car2(:,i)=sum(ar(6:10,i)); %vector,cumulated abnormal return of interval (-5,-1);
    car3(:,i)=sum(ar(10:12,i)); %vector,cumulated abnormal return of interval (-1,1);
    car4(:,i)=sum(ar(12:16,i)); %vector,cumulated abnormal return of interval (1,5);
    car5(:,i)=sum(ar(17:21,i)); %vector,cumulated abnormal return of interval (6,10);
    car6(:,i)=sum(ar(9:13,i)); %vector,cumulated abnormal return of interval (-2,2);
    car7(:,i)=sum(ar(8:14,i)); %vector,cumulated abnormal return of interval (-3,3);
    car8(:,i)=sum(ar(6:16,i)); %vector,cumulated abnormal return of interval (-5,5);
    car9(:,i)=sum(ar(1:21,i)); %vector,cumulated abnormal return of interval (-10,10);

ACAR=[mean(car1');mean(car2');mean(car3');mean(car4');mean(car5');mean(car6');mean(car7');mean(car8');me
an(car9')]; % mean cumulated abnormal returns
end
```

```
%% FOR INTERVAL P MATRIX AND ADJUSTED Z VALUE AND P VALUE
for i=1:21
   DE1=sqrt(inv(sum(SDE(:,1:5))));
   DE2=sqrt(inv(sum(SDE(:,6:10))));
   DE3=sqrt(inv(sum(SDE(:,10:12))));
   DE4=sqrt(inv(sum(SDE(:,12:16))));
   DE5=sqrt(inv(sum(SDE(:,17:21))));
   DE6=sqrt(inv(sum(SDE(:,9:13))));
   DE7=sqrt(inv(sum(SDE(:,8:14))));
   DE8=sqrt(inv(sum(SDE(:,6:16))));
   DE9=sqrt(inv(sum(SDE(:,1:21))));
   BETAH1=inv(sum(SDE(:,1:5)))*sum(NU2(:,1:5));
   BETAH2=inv(sum(SDE(:,6:10)))*sum(NU2(:,6:10));
   BETAH3=inv(sum(SDE(:,10:12)))*sum(NU2(:,10:12));
   BETAH4=inv(sum(SDE(:,12:16)))*sum(NU2(:,12:16));
   BETAH5=inv(sum(SDE(:,17:21)))*sum(NU2(:,17:21));
   BETAH6=inv(sum(SDE(:,9:13)))*sum(NU2(:,9:13));
   BETAH7=inv(sum(SDE(:,8:14)))*sum(NU2(:,8:14));
   BETAH8=inv(sum(SDE(:,6:16)))*sum(NU2(:,6:16));
   BETAH9=inv(sum(SDE(:,1:21)))*sum(NU2(:,1:21));
   BETAH=[BETAH1,BETAH2,BETAH3,BETAH4,BETAH5,BETAH6,BETAH7,BETAH8,BETAH9];
   Z41=DE1*sum(NU2(:,1:5));    % Z value for interval (-10,-6);
   Z42=DE2*sum(NU2(:,6:10));    % Z value for interval (-5,-1);
   Z43=DE3*sum(NU2(:,10:12));   % Z vlaue for interval (-1,1);
   Z44=DE4*sum(NU2(:,12:16));    % Z value for interval (1,5);
   Z45=DE5*sum(NU2(:,17:21));    % Z value for interval (6,10);
   Z46=DE6*sum(NU2(:,9:13));     % Z value for interval (-2,2);
   Z47=DE7*sum(NU2(:,8:14));     % Z value for interval (-3,3);
   Z48=DE8*sum(NU2(:,6:16));     % Z value for interval (-5,5);
   Z49=DE9*sum(NU2(:,1:21));     % Z value for interval (-10,10);
   Z4=[Z41,Z42,Z43,Z44,Z45,Z46,Z47,Z48,Z49];
   p4=2*(1-normcdf(abs(Z4)));
end
%% performance
DAILY=[betah;Z];
DAILY=DAILY(:);      %Adjusted results for daily ASAR, Z test and p value
INTERVAL=[BETAH;Z4];
INTERVAL=INTERVAL(:);  %Adjusted results for interval ASCAR, Z test and p value
```

A.3.3. Matlab Coding for GLS-2 Estimation

```
%% INPUT: RC1,RM1,testRC1,testRM1,LIST
RC=RC1';  % return matrix for securities in estimation period;
RM=RM1';  % return matrix for market indices in estimation period;
testRC=testRC1'; % return matrix for securities in test period;
testRM=testRM1';  % return matrix for market indices in test period;
% LIST is  multilist vector.
%% For studentized STAR
A=size(RC); % A(1) refers to number of days in estimation period, A(2) refers to number of securities.
for i=1:A(2); % i refers to columns of the matrix (number of securities)
   [b(:,i),bint,r,rint,stats] = regress(RC(:,i),[ones(A(1),1),RM(:,i)]); % regression function with market model
   er=RM.*b(2,i)+b(1,i);
   Ear(:,i)=RC(:,i)-er(:,i);  % residuals, abnormal return of estimation period
   X1=[ones(A(1),1),RM(:,i)];
   H=X1*inv(X1'*X1)*X1';
   hi=diag(H);
   segmahat2=sum(Ear'.^2)/(A(1)-2);  %the estimate of segmahat2 for internally studentized residuals
   sjt2(:,i)=((segmahat2'.^0.5).*((1-hi)).^0.5); % denominator of studentized residuals
   STAR=Ear./sjt2;   % studentized residuals
end
%% FOR OMEGA
OMEGA=corrcoef(STAR);   %% correlation matrix of abnormal return.
G=size(STAR);  % Size of the abnormal return matrix.
Multi=eye(G(2));   %Identity matrix.
%%
for i=1:(G(2)-1);
   if LIST(i+1,1)==LIST(i,1);
      Multi(i+1,i)=1;
   end
end
for i=1:(G(2)-2);
    if LIST(i+2,1)==LIST(i,1);
        Multi(i+2,i)=1;
    end
end
for i=1:(G(2)-3);
   if LIST(i+3,1)==LIST(i,1);
        Multi(i+3,i)=1;
   end
end
Multi=0.5*(Multi+transpose(Multi));
OMEGA(~Multi)=0;  %% correlation matrix with only multi-listing coefficients.
P= chol(inv(OMEGA));  % omega inverse matrix 213x213
%% FOR DAILY Z VALUE AND P VALUE OF ABNORMAL RETURNS
L=A(1);
rbarm=sum(RM)/L;
for i=1:A(2); % i refers to columns of the matrix (number of securities)
   B(:,i) =sum((RM(:,i)-rbarm(:,i)).^2);
   C(:,i)=(testRM(:,i)-rbarm(:,i)).^2;
   D(:,i)=1+1/L+C(:,i)/B(:,i);
   [b(:,i),bint,r,rint,stats] = regress(RC(:,i),[ones(L,1),RM(:,i)]); % regression function with market model
   s2(:,i)=stats(:,4);    % error variance for idividual security from market model(squared one)
   er=testRM.*b(2,i)+b(1,i);
   ar(:,i)=testRC(:,i)-er(:,i);  % abnormal return matrix
   AAR=mean(ar')';   %   mean abnorma returns on days
   sjt(:,i)=(s2(:,i).*D(:,i)).^0.5; % segma of idividual securities
   SAR=(ar./sjt);   % standardized abnormal returns 21x213
```

```
   SAR1=SAR';  % standardized abnormal returns 213x21
   ASAR=(1/A(2))*sum((ar./sjt)')';  % standardized abnormal returns for each day in test period
end
xtidea=ones(A(2),21)./sjt';  % standardized ones matrix 213x21
E=xtidea';   % standardized ones matrix (21x213)
%% FOR P MATRIX AND ADJUSTED Z VALUE AND P VALUE
for i=1:21;

ASCAR=[sum(ASAR(1:5))/sqrt(5),sum(ASAR(6:10))/sqrt(5),sum(ASAR(10:12))/sqrt(3),sum(ASAR(12:16))/sqrt(5),sum(ASAR(17:21))/sqrt(5),sum(ASAR(9:13))/sqrt(5),sum(ASAR(8:14))/sqrt(7),sum(ASAR(6:16))/sqrt(11),sum(ASAR(1:21))/sqrt(21)]';
  NU1(:,i)=inv(E(i,:)*P*xtidea(:,i));   % first part of numerater
  NU2(:,i)=E(i,:)*P*SAR1(:,i);    % second part of numerater
  DE(:,i)=sqrt(inv(E(i,:)*P*xtidea(:,i)));     % denominator
  SDE(:,i)=E(i,:)*P*xtidea(:,i);
  betah(:,i)=(NU1(:,i)*NU2(:,i));
  Z(:,i)=(NU1(:,i)*NU2(:,i))/DE(:,i);   %Z value of daily AAR
  p=2*(1-normcdf(abs(Z)));   %p value of daily AAR
end
% FOR CUMULATIVE Z AND p VALUE
for i=1:A(2),t=1:21;
   car1(:,i)=sum(ar(1:5,i)); %vector,cumulated abnormal return of interval (-10,-6);
   car2(:,i)=sum(ar(6:10,i)); %vector,cumulated abnormal return of interval (-5,-1);
   car3(:,i)=sum(ar(10:12,i)); %vector,cumulated abnormal return of interval (-1,1);
   car4(:,i)=sum(ar(12:16,i)); %vector,cumulated abnormal return of interval (1,5);
   car5(:,i)=sum(ar(17:21,i)); %vector,cumulated abnormal return of interval (6,10);
   car6(:,i)=sum(ar(9:13,i)); %vector,cumulated abnormal return of interval (-2,2);
   car7(:,i)=sum(ar(8:14,i)); %vector,cumulated abnormal return of interval (-3,3);
   car8(:,i)=sum(ar(6:16,i)); %vector,cumulated abnormal return of interval (-5,5);
   car9(:,i)=sum(ar(1:21,i)); %vector,cumulated abnormal return of interval (-10,10);

ACAR=[mean(car1');mean(car2');mean(car3');mean(car4');mean(car5');mean(car6');mean(car7');mean(car8');mean(car9')]; % mean cumulated abnormal returns
end
%% FOR INTERVAL P MATRIX AND ADJUSTED Z VALUE AND P VALUE
for i=1:21
   DE1=sqrt(inv(sum(SDE(:,1:5))));
   DE2=sqrt(inv(sum(SDE(:,6:10))));
   DE3=sqrt(inv(sum(SDE(:,10:12))));
   DE4=sqrt(inv(sum(SDE(:,12:16))));
   DE5=sqrt(inv(sum(SDE(:,17:21))));
   DE6=sqrt(inv(sum(SDE(:,9:13))));
   DE7=sqrt(inv(sum(SDE(:,8:14))));
   DE8=sqrt(inv(sum(SDE(:,6:16))));
   DE9=sqrt(inv(sum(SDE(:,1:21))));
   BETAH1=inv(sum(SDE(:,1:5)))*sum(NU2(:,1:5));  % Beta estimation of cumulative abnormal returns (-10,-6).
   BETAH2=inv(sum(SDE(:,6:10)))*sum(NU2(:,6:10)); % Beta estimation of cumulative abnormal returns (-5,-1).
   BETAH3=inv(sum(SDE(:,10:12)))*sum(NU2(:,10:12)); % Beta estimation of cumulative abnormal returns (-1,1).
   BETAH4=inv(sum(SDE(:,12:16)))*sum(NU2(:,12:16)); % Beta estimation of cumulative abnormal returns (1,5).
   BETAH5=inv(sum(SDE(:,17:21)))*sum(NU2(:,17:21)); % Beta estimation of cumulative abnormal returns (6,10).
   BETAH6=inv(sum(SDE(:,9:13)))*sum(NU2(:,9:13));  % Beta estimation of cumulative abnormal returns (-2,2).
   BETAH7=inv(sum(SDE(:,8:14)))*sum(NU2(:,8:14));  % Beta estimation of cumulative abnormal returns (-3,3).
```

```
   BETAH8=inv(sum(SDE(:,6:16)))*sum(NU2(:,6:16));  % Beta estimation of cumulative abnormal returns (-5,5).
   BETAH9=inv(sum(SDE(:,1:21)))*sum(NU2(:,1:21));  % Beta estimation of cumulative abnormal returns (-10,10).

BETAH=[BETAH1,BETAH2,BETAH3,BETAH4,BETAH5,BETAH6,BETAH7,BETAH8,BETAH9]; %Beta matrix for cumulative abnromal returns.
   Z41=DE1*sum(NU2(:,1:5));    % Z value for interval (-10,-6);
   Z42=DE2*sum(NU2(:,6:10));    % Z value for interval (-5,-1);
   Z43=DE3*sum(NU2(:,10:12));   % Z vlaue for interval (-1,1);
   Z44=DE4*sum(NU2(:,12:16));    % Z value for interval (1,5);
   Z45=DE5*sum(NU2(:,17:21));    % Z value for interval (6,10);
   Z46=DE6*sum(NU2(:,9:13));     % Z value for interval (-2,2);
   Z47=DE7*sum(NU2(:,8:14));     % Z value for interval (-3,3);
   Z48=DE8*sum(NU2(:,6:16));     % Z value for interval (-5,5);
   Z49=DE9*sum(NU2(:,1:21));     % Z value for interval (-10,10);
   Z4=[Z41,Z42,Z43,Z44,Z45,Z46,Z47,Z48,Z49];  % Z value matrix for cumulative abnormal returns.
   p4=2*(1-normcdf(abs(Z4)));   %p value of Z values
end
%% performance
DAILY=[betah;Z];
DAILY=DAILY(:);      %Adjusted results for daily abnormal returns and Z value.
INTERVAL=[BETAH;Z4];
INTERVAL=INTERVAL(:);     %Adjusted results for interval abnormal returns and Z value.
```

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