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Abstract

This study examines the relationship between stock market reaction to horizontal merger announcements and technical efficiency levels of the participating firms. The analysis is based on data pertaining to eighty mergers between firms in the U.S. manufacturing industry during the 1990s. We employ Data Envelopment Analysis (DEA) to measure technical efficiency, which capture the firms. competence to produce the maximum output given certain productive resources. Abnormal returns related to the merger announcements provide the investor.s re-evaluation on the future performance of the participating firms. In order to avoid the problem of nonnormality, heteroskedasticity in the regression analysis, bootstrap method is employed for estimations and inferences. We found that there is a significant relationship between technical efficiency and market response. The market apparently welcomes the merger as an arrangement to improve resource utilizations.

Journal of Economic Literature Classification: G14, C61, C15

TECHNICAL EFFICIENCY AND STOCK MARKET REACTION TO HORIZONTAL MERGERS

1. Introduction

A widely used index of the stock market reaction to a merger announcement is the rate of abnormal returns earned by the firms involved in the merger. Abnormal return is measured by the difference between realized return around the announcement and the normal return. This approach is often described as event study. Over the past two decades there have been numerous applications of the event study methodology in studying mergers and acquisitions[1]. Most studies focus on the *overall magnitude* of stock price reaction around the time of the announcement. But the *source* of any abnormal return is seldom explored empirically. Various theoretical studies have suggested expected elimination of the agency cost (Jensen, 1986), adoption of more efficient production or organizational technology, and realization of scale economies as possible reasons for abnormal returns associated with merger announcements. Others have attempted to explain the abnormal return differentials by method of payment (Travlos, 1987; Bower *et al.,* 2000), firm size, and level of industry concentration (Eckbo, 1985). Not much has been done, however, to link the fundamental measure of the firm's performance and the market evaluation of the firm around the date of merger announcement. This is especially true for the manufacturing industry, although some applications can be found in service industries (Alam and Sickles, 1998; Huang, 1999; Kohers *et al.,* 2000). The objective of

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[1] For a detailed review, refer to Jensen and Ruback (1983), Halpern (1983), Jarrell *et al. (*1988), and Andrade *et al.*(2001).

this paper is to investigate the relationship between stock market response to the merger announcement and the participating firms' technical efficiency. Technical efficiency measures a firm's managerial competence at combining inputs and outputs in its production process while the stock market returns reflect the investors' market evaluation based on the firm's fundamental value. If capital market is efficient, the stock returns can capture the expected economic gain from the proposed merger. This study is designed to examine if and how the technical efficiencies of the participating firms affect the market's assessment of merger potentials focusing on the empirical evidence from the U.S. manufacturing industry in the 1990s.

For this, we first compute the abnormal return of each firm in the sample using the traditional event study analysis. Simultaneously, we employ Data Envelopment Analysis (DEA) to calculate the technical efficiency of each firm one year before the mergers announcement[2]. In the next stage, the event-related abnormal returns are regressed on several explanatory variables, which include technical efficiencies and other control variables using data from firms involved in mergers over the study period. Inferences about the relationship between abnormal returns and firm specific characteristics are drawn from the results of these regressions. One problem is that statistical tests strongly reject the assumptions of homoscedasticty and normality of the regression disturbances. This, of course, invalidates the usual tests of significance of the regression coefficients. To overcome this problem, we employ the bootstrap

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[2] DEA has also been used to measure managerial ability in bank evaluations known as CAMEL (Barr *et al.*, 1993). The evaluation factors are: capital adequacy, asset quality, management quality, earnings ability and liquidity.

methodology. The results show that abnormal returns are strongly related with efficiency levels of both the bidding firms and the targets.

This paper contributes to the literature in several ways. First, we perform a distribution-free test of significance of the regression of abnormal returns on technical efficiency of the firms involved. Second, we add to the limited number of studies that attempt to explore the relation between the technical efficiency and the market valuation of a firm. Moreover, it is the first application of DEA coupled with event study to manufacturing industries.

The rest of the paper is organized as follows. Section two reviews the relevant empirical literature on the event studies and the cross-sectional regressions. Section three outlines the methodologies for event study, Data Envelopment Analysis (DEA), and bootstrapping in regression analysis. Section four describes the datasets and the empirical results and section five concludes.

2. Literature Review

In the financial economics literature, it is common to employ an event study approach to analyze the impact of a merger "event" upon the stock price performance of both the targets and acquirers. This strand of research is based on the assumption that the stock market is efficient[3]. Market efficiency means that actual market prices incorporate all available information and that the actual market return of an asset is the intrinsic economic return of the firm (Fama, 1970 and 1991). Therefore, any deviation from the

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[3] There are three forms of market efficiency in the financial literature: (1) weak form of the market efficiency, that is, the capital market can reflect all the past information; (2) semi-strong form of the market efficiency, that is, the stock prices can reflect public information announcement; (3) strong form of the

normal or expected return, known as the abnormal return, reflects the effect of the merger event upon the participating firms, and it can be regarded as the change in the valuation of the firm resulting from the merger. Jensen and Ruback (1983) reviewed a number of studies of the stock prices of the participating firms for both successful and unsuccessful mergers in the 1980s. The evidence indicated that target firms in successful takeovers experienced statistically significant abnormal stock price increases while bidding firms realized small but sometime insignificantly negative changes[4]. The overall effect for acquiring firms is not clear. There were insignificant stock price changes for the unsuccessful takeovers for the target firms. These empirical studies do not restrict themselves to horizontal mergers between firms within the same industry. They generally examine mergers by analyzing the data from a several-week time "window" around a merger announcement. Scherer (1988) argued that when the time frame was extended to one to three years after the merger event, acquiring firms are found to experience negative abnormal returns. However, a long-run study often confounds the effects of various events that occur over the longer time horizon with the effect of the merger event itself. As a result, the variance is usually high and the negative abnormal returns often turn out to be insignificant.

Although the overall market reaction to merger announcements are generally recognized, proper understanding of the association between the magnitude of the abnormal return to each merger event and specific sources is still limited. Various theoretical sources of gains to takeovers have been suggested. They include: (1) synergies such as potential reductions in production or distribution costs; (2) financial benefits,

market efficiency, that is, the stock price can reflect the private information. The semi-strong form of the market efficiency is employed in the event study literature.

including the use of tax shields, avoidance of bankruptcy costs and other types of tax advantages; (3) elimination of managerial inefficiency; (4) anticompetitive motivations; and (5) wealth redistribution. Auerbach and Reishus (1987) studied 318 mergers and acquisitions during 1968-83 to estimate tax benefits and found that tax benefits play a minor role in explaining merger and takeover activities. Jarrell *et al.* (1988) reviewed most of the redistribution theories about the source of merger gains. They found that none of those hypotheses was supported by the empirical evidence and concluded that the merger gains primarily reflected economically beneficial reshufflings of productive assets and managements. Eckbo (1985) used capital market data to test the market concentration theory, and found that industry wealth effect is not correlated with the change in concentration nor the pre-merger concentration level.

Travlos (1987) provides a direct link between the different stock returns towards merger proposal announcement and the methods of payment of bidding firms. He found that acquirers with pure stock payment experienced significant losses while others on cash payment earned the normal rate of return. Bower *et al.* (2000) investigated the bidders' and targets' perspectives towards the financial slack and mode of payments in corporate acquisitions. They found that bidders with financial slacks but using common stock experienced lower abnormal returns at the merger announcement date.

Alam and Sickles (1998) analyzed the association between stock market returns and relative technical efficiency in airline industry. The technical efficiency measured by DEA served as the proxy for the firms' managerial ability . Although they did not directly study mergers and acquisitions in this industry, their results are, nevertheless, relevant in the present context because they show that there exists both a statistically and an

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[4] Bidders and acquirers are used interchangeably in this paper.

economically significant relationship between technical efficiency changes and market returns. The correlation between technical efficiency and stock returns appears in the two month after the disclosure of the financial data.

Huang (1999) and Kohers *et al.* (2000) investigated the stock market perception of technical efficiency of the targets to bank merger announcements during the 1990s. They adopted both DEA and Stochastic Frontier Approaches (SFA) to evaluate efficiency of the acquired banks[5]. Then the efficiency levels of the targets and other control variables are used to explain the bidder's cumulative abnormal returns (CAR) on the date of merger announcement. They concluded that the efficiency in general could explain most of the abnormal returns of the stock price.

3. Methodology

3.1 Event Study Methodology

The 'event study' methodology, inspired by Fama *et al.* (1969) and Ball and Brown (1968), utilizes stock market data to measure the impact of an event on the participating firms over a certain period as the deviation of the stockholders' actual rate of return from its expected returns based on a particular value generating process. Those "unusual" behavior of the stock returns lead to what is known as abnormal returns

$$AR_{it} = R_{it} - E(R_{it} \mid X_t) \tag{1}$$

where AR_{it}, R_{it}, and $E(R_{it} \mid X_t)$ are, respectively, the abnormal, actual, and normal returns for firm i at time t. X_t is conditioning information for the normal return model[6].

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[5] For Stochastic Frontier Approach, refer to Kumbhakar and Lovell (2000).
[6] X_t includes all available information at time *t* other than the event.

Hence abnormal returns provide information about the investors' re-evaluation of the stream of expected income from a stock given certain event. The fundamental assumption behind this approach is that capital markets are efficient with respect to publicly available information such as a merger announcement[7].

The first step in conducting an event study is to define the event of interest and to identify the period over which the stock prices of the firms involved in this event will be examined. This is called an event window. In the case of mergers and acquisitions, the event date is the merger and acquisition announcement date. Conventionally, the event date is set as $t = 0$, and a time period around the event date is used to aggregate abnormal returns on the individual stock. The time line for an event study is shown in Figure 1 (MacKinlay, 1997:20). The time period between T_0 and T_1 is estimation window and T_1 and T_2 is the event window.
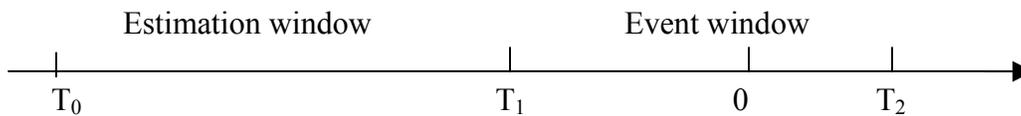
Figure 1. Time line for an event study

Typically, the estimation and the event windows do not overlap. The estimation window provides estimators for the parameters of the normal return model, which are not influenced by the returns around the event. The abnormal return is then calculated as the difference between the actual returns and what is predicted by the fitted model using the data from the event window (Mackinlay, 1997).

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[7] This is also known as the semi-strong form of the market efficiency hypothesis. See footnote 2 for detailed explanation of the market efficiency hypothesis.

3.1.1 Estimation of Abnormal Returns

The commonly used normal return model is the market model (Fama, 1976: chapter 3). It is based on the assumption that the joint distribution of all stock returns $(R_{1t}, R_{2t,...,} R_{nt})$ in the market is the multivariate normal distribution. Stock return at time t is defined as the ratio between the capital gain plus dividend and the initial price:

$$R_{it} = \frac{d_{it} + (p_{it} - p_{i,t-1})}{p_{i,t-1}} \qquad (2)$$

where d_{it} is the dividend per share of the common stock of firm i from the end of $t-1$ to the end of t, p_{it} is the market price at the end of t and $p_{i,t-1}$ is the market price at the end of $t-1$. The market return

$$R_{mt} = \sum_{i=1}^{n} x_{im} R_{it} \qquad (3)$$

is a linear combination of the individual stock returns that may be weighted either equally or by their respective market shares to construct the market return. By the normality assumption about the individual returns, the market return also has a univariate normal distribution. Therefore, the joint distribution of R_{it} and R_{mt} is the bivariate normal, and the expected return from a stock conditional on the market return is

$$E(R_{it} \mid R_{mt}) = \alpha_i + \beta_i R_{mt} \qquad (4)$$

where $\beta_i = \dfrac{Cov(R_{it}, R_{mt})}{V(R_{mt})}$, and $\alpha_i = E(R_{it}) - \beta_i E(R_{mt})$ \qquad (5)

Furthermore, the conditional variance $V(R_{it} \mid R_{mt})$ has the same value for all values of R_{mt}. Therefore, the relationship between R_{it} and R_{mt} can be expressed as

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad (6)$$

Besides, the deviations, ε_{it}, are normal with mean zero and variance independent of R_{mt},

that is, $E(\varepsilon_{it} \mid R_{mt}) = E(\varepsilon_{it}) = 0$ (7)

and $V(\varepsilon_{it} \mid R_{mt}) = V(R_{it} \mid R_{mt}) = V(R_{it})(1 - \rho_{im}^2) = V(\varepsilon_{it})$ (8)

where ρ_{im} is the correlation coefficient between R_{it} and R_{mt} and

$$\rho_{im} = \frac{Cov(R_{it}, R_{mt})}{\sqrt{V(R_{it})V(R_{mt})}}.$$ (9)

The properties of the bivariate normal distribution satisfy the classical assumptions of the

linear regression; therefore, OLS is generally used in the estimation of the parameters

$\hat{\alpha}_i, \hat{\beta}_i$ in the market model based on the data in the estimation window. The abnormal

return is calculated using data in the event window as

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt})$$ (10)

where t belongs to the event period.

A traditional event study usually aggregates abnormal returns cross-sectionally

through the relative time period to the event date. Given that firms in the sample are

independent and there is no overlap between the event dates, the average abnormal return

(AAR) and its variance are given by

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it}$$ (11)

$$V(AAR_t) = \frac{1}{N^2} \sum_{i=1}^{N} \hat{\sigma}_i^2$$ (12)

where N is the number of firms in the sample and $\hat{\sigma}_i^2$ is the estimated variance for each

firm i. Also, for a specific choice of the event window (T_1, T_2), the cumulative abnormal

return and its variance are calculated as:

$$CAR = \sum_{t=T1}^{T2} AAR_t \tag{13}$$

$$\text{and } V(CAR) = \sum_{t=T1}^{T2} V(AAR_t) \tag{14}$$

where t belongs to the event window[8]. Usually the 't' statistic utilized to test whether average (or cumulative) abnormal return is significantly different from 0. It is well known that validity of the t test rests on the normality assumption. In reality, the individual daily stock returns may not be normally distributed. However, one may appeal to the Central Limit Theorem to justify using the t test. Besides, Brown and Warner (1980, 1985) also conclude that when the cross sectional sample size exceeds fifty, the aggregated average daily return is approximately normal (Brown and Warner, 1985).

3.1.2 Cross-sectional Model

The average abnormal returns capture the impact of a particular event on stock returns in general on any day within the event window; similarly, cumulative abnormal returns provide the overall effect over pre-specified event window. However, each independent announcement has different market reaction. In order to single out the sources of the abnormal return differentials, a cross-sectional model is usually employed. The model is

$$CAR_i = F(x_1, x_2, ... x_m) + u_i \tag{15}$$

where CAR_i is the cumulative abnormal return for firm i over a pre-specified event window, x_is refer to some firm-specific characteristics that contribute to the different

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[8] See Figure 1.

market reaction and u_i is an added noise. The simplest model to capture the differences of the abnormal returns is the linear functional relationship, that is,

$$CAR_i = \delta_0 + \delta_1 x_1 + \delta_2 x_2 ... + \delta_m x_m + u_i,$$ (16)

where CAR_i is the cumulative abnormal return for ith observation, δ_j s are the coefficients, and $E(u_i) = 0$. If the errors of equation (16) satisfy homoscedasticity and cross-sectional independence, it can be easily estimated by OLS. But the standard statistical tests of significance of the estimated coefficients presuppose a normal distribution of the disturbance term. Homoscedasticity and normality are quite strong assumptions in the context of stock market data. Therefore, in this study, we employ a bootstrap procedure in order to perform significance tests without making these assumptions.

3.2 Bootstrap

Efron (1979) introduced the bootstrap procedure as a method of constructing the sampling distribution of a statistic through resampling from the observed data. It arises from an analogy in which the observed data assume the role of an underlying population. In an ideal setting in which many samples can be drawn from the underlying population F, one could compute the statistic from each sample and estimate its variability across samples directly. However, it is usually not possible to draw repeated samples from the population. So an optimal approximation of F is the empirical distribution F_n defined as:

$$F_n(x) = \#(x_i \leq x) / n$$ (17)

where $\#(x_i \leq x)$ is the number of times that the inequality holds as i ranges from 1 to n.

That is, $F_n(x)$ is the proportion of the sample observations that are less than or equal to x.

The bootstrap procedure is to resample with replacement from the empirical distribution, and then apply the original estimator to each resampled data so that resulting estimates mimic the sampling distribution of the original estimator. Suppose the observed data $X = (x_1, x_2, ..., x_n)$ constitute a random sample drawn from some unknown distribution F and the statistic of interest $\hat{\theta} = f(x_1, x_2, ..., x_n)$ is based on this sample. The empirical distribution F_n yields the bootstrap samples $X^* = (x^*_1, x^*_2, ..., x^*_n)$ through random sampling. From these we calculate bootstrap replications of the statistic of interest, $\hat{\theta}^* = f(x^*_1, x^*_2, ..., x^*_n)$. Rather than having samples in which $x_i \sim F$, we have bootstrap samples in which $x^*_i \sim F_n$. Then the distribution of $\hat{\theta}^*$ around $\hat{\theta}$ in F_n is the same as of $\hat{\theta}$ around θ in F. That is:

$$(\hat{\theta}^* - \hat{\theta}) | F_n \sim (\hat{\theta} - \theta) | F \tag{18}$$

The big advantage of the bootstrap is that we can calculate as many replications of $\hat{\theta}^*$ as we want, or at least as many as we can afford. This allows us to calculate the usual statistical properties of the estimator, such as the mean, variance and confidence interval, especially when it is not possible to analytically derive the sampling distribution of the statistic $\hat{\theta}^*$. The mean and standard error of the bootstrap estimator are:

$$E(\hat{\theta}_b^*) = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}^*_b \tag{19}$$

$$se(\hat{\theta}_b^*) = \sqrt{\frac{1}{B-1} \{\hat{\theta}^*_b - E(\hat{\theta}^*_b)\}^2} \tag{20}$$

where b refers to the bth bootstrap replicate $(b = 1,2,...,B)$.

Bootstrap estimators in general are biased. The bias of the bootstrap estimator is given by (Efron and Tibshirani, 1993):

$$bias(\hat{\theta}_b^{*}) = E(\hat{\theta}^*{}_b) - \hat{\theta} \tag{21}$$

Based on the bootstrap bias, the bias-corrected estimator of θ is:

$$\hat{\theta}^*{}_{bc} = \hat{\theta} - bias = 2\hat{\theta} - E(\hat{\theta}^*{}_b) \tag{22}$$

Finally, we can use the percentile method to construct the $(1-2\alpha)\%$ confidence interval for the θ based on the bias-corrected estimator $\hat{\theta}^*{}_{bc}$. There are alternative ways to generate bootstrap samples. We describe below two of the most commonly applied bootstrap methodologies are (i) the naive bootstrap and (ii) the smoothed bootstrap. For reasons given below, we employ a different bootstrap procedure known as the wild bootstrap for significance test of the regression coefficients in this study.

3.2.1 Naïve bootstrap Methodology

In a naïve bootstrap samples are drawn from original data through repeated sampling with replacement. Suppose a sample of observed data $X = (x_1, x_2,...,x_n)$ is drawn randomly from some population with an unknown probability distribution F. The bootstrap sample $X^* = (x_1^*, x_2^*,..., x_n^*)$ is an unordered collection of n elements drawn randomly from the original sample X of the same size with replacement. Because each bootstrap sample consists of n observations that are drawn with replacement from the data, each bootstrap sample typically omits several observations from the original sample

and includes multiple replications of others. Therefore, a bootstrap sample will not include any observation from the underlying population that was not drawn in the original sample. This is a major limitation of the naïve bootstrap procedure. One consequence of this is that unlike smooth distributions, an empirical distribution of the bootstrap sample has a "jump" at each observed value. The jumps reflect the fact that only n distinct values are possible from this approximation to the true population F. Although the bootstrap samples generally resemble the underlying distribution, they fail to reflect the fact that the underlying distribution is continuous.

3.2.2 Smooth Bootstrap Methodology

One way to overcome the problem of the naïve bootstrap is to use kernel density estimation to smooth the empirical distribution. A kernel-smoothed estimator is provided

by: $F_n(t) = \dfrac{1}{nh} \sum_{i=1}^{n} K(\dfrac{t - x_i}{h})$ (23)

where the h is the smoothing parameter and is also known as the bandwidth in kernel density estimation, K is typically the standard normal probability density function. By convolution theorem (Efron and Tibshirani, 1993), it is easy to show that

$t_i = x_i + h\xi_i$ (24)

where x_i is the observed value in the sample and ξ_i is a random deviate drawn from the standard normal distribution.

A smoothed bootstrap sample is generated from a given sample $X = (x_1, x_2, ..., x_n)$ by the following algorithm (Silverman, 1986):

(1) Generate a naïve bootstrap sample $X^* = (x_1^*, x_2^*, ..., x_n^*)$ from the original data.

(2) Generate ξ_i from the specified (standard normal density function) K.

(3) Set $x_i^s = x_i^* + h\xi_i$, where h is the smoothing parameter.

The smoothed bootstrap requires a choice of an appropriate bandwidth h. Usually the optimal h is obtained by minimizing the approximate mean integrated square error. However, this h itself depends on the unknown density function to be estimated. A natural approach is to choose h with reference to some standard family of density functions, such as the normal densities. For the normal density and a Gaussian kernel, the optimal h is proportional to $n^{-1/5}$. Following Silverman (1986), a good approximation can be obtained at

$$h = 0.9An^{-1/5} \tag{25}$$

where A= min{standard deviation, interquartile range/1.34}.

3.2.3 Bootstrapping a Regression Model

In the regression model (16) outlined in section 3.1.2, the classical assumptions about the random error are usually violated and the problems of non-normality, heteroscedasticity, and cross-sectional correlation are endemic. Therefore, the test statistics for the coefficients are generally not valid. A possible approach to address the heteroscedasticity problem is to use the Heteroscedasticity Consistent Covariance Matrix Estimator (HCCME) (Eicker, 1963 and 1967; White, 1980). It should be noted, however, that the resulting variance estimates of the coefficients may be seriously biased downward (Greene, 2000: 507)[9]. In that sense, the White estimator is overly optimistic and the test statistic is likely to exceed the nominal level, especially in small samples.

Moreover, GLS estimators depend crucially on the weight used and using the wrong set of weights can also cause new problems. Standard errors associated with the improperly weighted least squares estimator will be incorrect. Even when the form of the heteroskedasticity is known but involves unknown parameters, the additional variation incorporated by the estimated variance parameters may offset the gains to GLS in small or moderate sized samples (Greene, 2000:522-523).

On the other hand, bootstrap requires few distributional assumptions about the disturbances in a regression model; hence the findings are less susceptible to violation of the model assumptions. There are three ways to bootstrap regressions: bootstrap based on residuals, paired bootstrap and external bootstrap or wild bootstrap (Shao and Tu, 1996: 291-292). The bootstrap (whether naïve or smoothed) applied to the sample of residuals from a fitted regression model will not be robust against heteroscedasticity since it is based on the i.i.d. assumption of the errors (Wu, 1986). By contrast, wild bootstrap and paired bootstrap procedures are robust against heteroskedastictiy (Liu, 1988; Mammen, 1993; Shao and Tu, 1996: 292-295). Paired bootstrap usually assumes that the design matrix X is random, and (Y, X) come from some joint distribution. Understandably, when the dimension of X gets large, it becomes unwieldy for empirical application. Moreover, paired bootstrap does not impose the restrictions that $E(u \mid x) = 0$ on the bootstrap samples. Also, a bootstrap design matrix X^* may not be of full rank even if the actual X is. The wild bootstrap offers a better alternative because it ensures $E(u \mid x) = 0$ and has a better numerical performance than paired bootstrap (Horowitz, 1997). The wild Bootstrap proceeds as follows.

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[9] For theoretical discussions, refer to Chesher and Jewitt (1987). For empirical simulation, see Jeong and

(1) First one estimates the regression (16) model by OLS and obtains the unbiased

estimator $\hat{\delta}_j$ s along the regression residual

$$\hat{u}_i = CAR_i - (\hat{\delta}_0 + \hat{\delta}_1 x_1 + \hat{\delta}_2 x_2 ... + \hat{\delta}_m x_m) \tag{26}$$

where $\hat{u}_i$ is the ith OLS residuals ($i = 1,2,...n$).

(2) For each i let F_i be the two-point distribution that satisfies:

$$E(z \mid F_i) = 0 \tag{27}$$

$$E(z^2 \mid F_i) = \hat{u}_i^{\;2} \tag{28}$$

$$E(z^3 \mid F_i) = \hat{u}_i^{\;3} \tag{29}$$

where z is a random variable with the CDF F_i. In this distribution, $z = \dfrac{(1-\sqrt{5})}{2}\hat{u}_i$ with

probability $\dfrac{(1+\sqrt{5})}{2\sqrt{5}}$, and $z = \dfrac{(1+\sqrt{5})}{2}\hat{u}_i$ with probability $1 - \dfrac{(1+\sqrt{5})}{2\sqrt{5}}$ [10].

(3) For each $i = 1,2,...n$, sample $u_i^{\;w}$ randomly from the distribution F_i.

(4) Compute the wild bootstrap abnormal returns by adding resampled residual $u_i^{\;w}$ onto

the least squares regression fit, holding the regressors fixed:

$$CAR^w{}_i = \hat{\delta}_0 + \hat{\delta}_1 x_1 + \hat{\delta}_2 x_2 ... + \hat{\delta}_m x_m + u^w{}_i \tag{30}$$

(5) Obtain bootstrap estimates $\hat{\delta}^w{}_j$ s from the model (16) using $CAR^w{}_i$ as the dependent

variable.

Maddala (1996), Horowitz (1997), and Cribari-neto and Zarkos (1999).

[10] This is one possible construction of F_i. For more alternatives see Mammen (1993).

(6) Repeat step (3) to (5) for b =1,…, B, and use the resulting bootstrap estimates $\hat{\delta}^1{}_j, \hat{\delta}^2{}_j, \hat{\delta}^3{}_j, ..., \hat{\delta}^B{}_j$ to estimate the bootstrap mean, variances, empirical percentile interval and empirical p-value.

3.3 Data Envelopment Analysis

Data Envelopment Analysis (DEA) was introduced by Charnes, Cooper, and Rhodes in 1978 as a nonparametric method of measuring a firm's technical efficiency[11]. Unlike the parametric approach, DEA does not assume any functional forms of the production, cost or profit function. In addition, it uses linear programming methods instead of the least square regression approach. DEA constructs a production possibility set from the observed input-output bundles of the firms in the sample with the following assumptions[12].

(A1) All actually observed input-output combinations are feasible.

(A2) The production possibility set is convex.

(A3) Inputs are freely disposable

(A4) Outputs are freely disposable.

Suppose that the input-output data are observed for n firms. Firm j produces the output bundle y^j using the input bundle x^j. It is possible to empirically construct a production possibility set satisfying assumptions (A1-A4) from the observed data set without any explicit specification of a production function. Consider the input-output pair $(\hat{x}, \hat{y})$

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[11] The nonparametric approach to measuring technical efficiency was introduced by Farrell (1957).
[12] These are fairly weak assumptions and hold for all technologies represented by a quasi-concave and weakly monotonic production function.

where $\hat{x} = \sum_{1}^{N} \lambda_j x^j$, $\hat{y} = \sum_{1}^{N} \lambda_j y^j$, $\sum_{1}^{N} \lambda_j = 1$, and $\lambda_j \geq 0$ ($j = 1,2,...,N$). By (A1-A2),

$(\hat{x}, \hat{y})$ is feasible. Now, by (A3), if $x \geq \hat{x}$, then $(x, \hat{y})$ is also feasibly. Next, by (A4), if

$y \leq \hat{y}$, then $(x, \hat{y})$ is feasible. Thus, using (A1-A4), we can construct the production

possibility set with variable returns to scale:

$$T = \{(x,y) : x \geq \sum_{1}^{N} \lambda_j x^j; y \leq \sum_{1}^{N} \lambda_j y^j; \sum_{1}^{N} \lambda_j = 1; \lambda_j \geq 0(j = 1,2...,N)\}.^{13} \quad (31)$$

Using the above production possibilities set, we can measure the output-oriented

technical efficiency of firm s producing output y^S from the input bundle x^S as

$$TE_O^S = \frac{1}{\varphi^*} \quad (32)$$

where

$$\varphi^* = \max \varphi : (x^S, \varphi\, y^S) \in T. \quad (33)$$

The DEA model for measuring output-oriented efficiency under the assumption of

variable returns to scale is[14]:

$$\text{Max } \varphi$$

$$\text{S.T. } \sum_{i=1}^{n} \lambda_i y_i \geq \varphi y^S \quad (34)$$

$$\sum_{i=1}^{n} \lambda_i x_i \leq x^S$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

$$\lambda_i \geq 0.$$

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[13] This is known as BCC model due to Banker *et al.* (1984).
[14] Similarly input-oriented technical efficiency can also be computed based on DEA. For information about various DEA models, see any standard book on DEA book (e.g., Ray (2004)).

Technical efficiency of each firm captures the firm's managerial competence to produce the maximum amount of output from a given available resources.

4. Empirical Evidences and Discussion

4.1 Data and Data Construction

Three datasets are employed in this research. The first is the roster of the mergers and acquisitions obtained from Thomson Financial's Worldwide Merges & Acquisitions Database. The second dataset consists of the daily stock returns for both bidders and targets and the corresponding market returns around the announcement date, which are available from Center for Research in Security Prices (CRSP) database. The equal-weighted CRSP market return is used to capture the general market conditions. The other dataset containing the firm level financial information from the relevant industries for each merger, came from Compustat. Each merger included in the sample satisfies the following selection criteria: (1) both acquirers and targets are publicly traded companies, which ensures that the financial information is available for those firms; (2) both acquirers and targets are from the U.S. manufacturing industry (the two-digit SIC codes between 20 and 38); (3) the deals are horizontal mergers, that is, the acquirer and target have the same two-digit SIC code; (4) the sample period is from 1990 to 1999; (5) all the deals are one hundred percent acquisitions; (6) the financial information of the firms should be available for the year before the merger announcement date; (7) the stock price information is available for the bidder and the target firm around the announcement date. For firms with multiple merger announcement events, each event is treated as separate A

firm with another merger announcement within six months of the announcement date is eliminated. Eighty transactions met these criteria.

Three inputs, labor (L), capital (K) and materials (M), and one composite output (Y) are used in the output-oriented DEA model. Input and output quantities are not directly available from the Compustat but can be constructed indirectly from the financial data. The labor input (L) is measured by the number of full-time employees (in thousands). Following Christensen and Greene (1976) and Morrison (1999), the capital (K) is treated as flow input and is measured by the sum of depreciation, amortization and interest expenses deflated by the rental price of the capital. The rental price of capital is defined as: $P_k \times (r + d)$, where P_k is the price of the capital (measured by the producer price index for capital good); r refers to the real interest rate (measured by the average interest rate on long-term corporate bonds deflated by the inflation rate obtained from the producer price index); and d is the depreciation rate (a ten percent rate of depreciation is used for all the industries).

Total output is constructed by adjusting sales for changes in the inventories of finished goods. Different deflators were used for opening inventories, sales, and closing inventories.

The following procedure was followed to construct a quantity index for the raw material input (M). The total expense on materials was approximated by the difference between the total cost of good sold and total wages paid. Total wage payment is estimated by multiplying the total number of employees by the average production labor cost can be obtained from the Annual Survey of Manufactures for each industry. The raw material

expenditure deflated by the producer price index[15] of raw materials is used as a   quantity

index of the material input.

4.2 Event Study Analysis: Overall Results

We start off with the traditional event study outlined in section 3.1 in order to

get the abnormal return for each participating firm. The estimation window begins 126

trading days before for the bidding firms and 183 days for the target firms, and ends 16

days before the merger announcement[16]. Firm specific values of $(\hat{\alpha}_i, \hat{\beta}_i)$ were estimated

from the data in estimation window using the market model in equation (6). The event

window covers fifteen days prior to and fifteen days following the merger announcement

date[17]. In order to assess the validity of OLS regression for the market model, different

tests were performed with the residuals from regression[18]. While the residuals do not

violate the linearity assumption, they do not conform well to the normality assumption.

Despite the violation of the normality assumption, however, the least squares estimators

remain unbiased and consistent. Overall, 80 percent of the acquiring firms do not exhibit

any autocorrelation or heteroscedasticity (either cross-sectional or temporal, i.e., auto-

regressive conditional heteroscedasticity (ARCH). For target firms, two thirds of the

regressions satisfy the OLS assumptions. Therefore, given the reasonably large sample

size[19], OLS regression is not inappropriate for this dataset.

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[15] All price indexes used in this study were obtained from various tables published by Bureau of Labor Statistic (BLS).

[16] Travlos (1987) also use the estimation period 16 days prior to the announcement of the merger.

[17] See figure 1 for the event study time line.

[18] While the market model has its advantage of simplicity and robustness, it has been subjected to a lot of criticism for not accounting for changes in the parameters during the event window, arbitrarily determining the event period and violation the assumption of OLS regression.

[19] Brown and Warner (1985) concluded that the average abnormal return is close to the normal distribution if the sample size is greater than fifty.

In order to avoid the problem of arbitrary choices of the event period, average and cumulative abnormal returns were computed for event windows at different length.[20] The AAR, CAR and 't' statistics are calculated according to equation (11) and (13). Table 1 reports the stock return at one-month interval around the merger announcement date. For acquirers, the event date (t =0) abnormal return is significantly less than zero (t ratio = 4.3), while for targets it is significantly greater than zero. This is not inconsistent with the existing literature[21].

4.3 Cross-sectional Analysis

The purpose of the cross-sectional analysis is to link the market reaction to merger announcement with the technical efficiency of the participating firms. The models examine if and in what manner is the stock market reaction toward a merger announcement related to the technical efficiency levels of the firms involved in the merger. In order to measure the different impact on the acquiring and the target firms, the following two cross-sectional regressions are specified:

$$CAR_i\_tag = \alpha_0 + \alpha_1 Phi1 + \alpha_2 Phi2 + \alpha_3 PM + \alpha_4 CR$$

$$+ \alpha_5 Log(size1) + \alpha_6 Log(size2) + u_{1i} \qquad (35)$$

$$CAR_i\_acq = \beta_0 + \beta_1 Phi1 + \beta_2 Phi2 + \beta_3 PM + \beta_4 CR$$

$$+ \beta_5 Log(size1) + \beta_6 Log(size2) + u_{2i}. \qquad (36)$$

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[20] The results are available from the authors on request. The plots of the average abnormal returns and cumulative abnormal return also show that the market uses the merger announcement information to make a new assessment for shares of the participants.
[21] See Jensen and Reback (1983) for a detailed review.

Note that in this model, CAR_i_tag and CAR_i_acq are three-day cumulative abnormal return (t = -1,0,1) for the target and acquiring firms respectively. Three-day cumulative abnormal returns reflect the immediate impact of the merger announcements, and it also creates a sufficient gap between estimation window and event window to clearly separate these two. On the day before the merger announcement, there may be information leakage due to market anticipation or other private gossip, while in some cases the merger announcement is made at a late hour in the trading day, so that the market does not have enough time to react the new information within the same day. Consequently, the stock price on the day following the announcement may still contain valuable information. Therefore, the cumulative abnormal return over the three-day abnormal returns can provide better information than the one-day abnormal return. Phi1 and Phi2 are the inverse of the output-oriented technical efficiency of the acquirers and targets, respectively, obtained from the optimal solution of the model in (34) in section 3.3. They represent the potential increase in output in the acquiring and the target firm, respectively. Because the market evaluates a firm on the basis of its past performance, Phi1 and Phi2 are computed from data pertaining to one year prior to the merger announcement date. PM is a dummy variable for the method of payment. It assumes the value unity if the transaction is financed by cash or mixture of cash and others, and zero otherwise. It has been found that payment method in mergers and acquisition can affect the market re-evaluations of the two participants and, generally, stock return favors the cash offer (Bowers, *et al.*, 2000; Travlos, 1987). CR represents the industry specific four-firm concentration ratio prior to the merger and is included because it plays an important part in the determination of the legality of the horizontal mergers (Eckbo, 1985). Log

(size1) and Log (size2) are the logarithm of the size of the acquiring firm and target firm, respectively. We use total assets of a firm to measure its size.

The summary statistics of the regression data are shown in table 2. The models in (35) and (36) are both estimated by OLS regression and the fitted models reported in Table 3. Before using the estimates and their standard errors for hypothesis testing, we tested the residuals for normality and against heteroscedasticity. As can be seen from the test statistics reported in Table 4, the normality assumption is strongly rejected in the case of the regression for the acquiring firms by each of the tests employed. For the target firms, the normality of residuals was rejected at 10 % or lower levels of significance by all tests except the Kolmogrov-Smirnov test. Further, the homoscedasticity assumption was rejected by the White test at the 5% significance level for both regressions. In light of these results, the usual 't' tests of significance of the regression coefficients are of questionable validity. The wild bootstrap procedure described in section 3.2.3 provides a distribution-free test of significance of the individual regression coefficients. The bootstrap regression estimates for acquirers and targets are listed in Tables 5 and 6, respectively. The results of each regression using OLS are also shown in these two tables for comparison. For the wild bootstrap, apart from the means we also report the various quantiles of the empirical distribution of the coefficients. We conclude that a coefficient is significant at the 5% level in a two-tailed test of significance if the interval covering the 2.5 percentile and the 97.5 percentile of the distribution does not include zero[22]. We also report in the same table the p-values for the one-tailed tests of significance of the coefficients. In the context of the bootstrap this p-value is measured by the proportion of

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[22] If the interval covering the 5% percentile and the 95% percentile of the distribution does not include zero, we conclude that a coefficient is 10% significantly different from zero.

the bootstrap replications in which the coefficient lies on the other side of zero[23]. Besides, the empirical distributions of the coefficients from the bootstrap replications are also shown in Figure 2.

While the OLS and the estimated coefficients from the OLS and the wild bootstrap regressions are quite close to one another, differences in their sampling distribution do lead to different conclusions from the tests of significance in a number of cases. For example, in the regression for the acquiring firms, the coefficient of Phi2 is significantly different from 0 at the 5% level in the OLS regression. But in the case of the bootstrap regression, the coefficient is not significant even at the 10% level. In deed, it is not found to be significantly negative even in a one-tailed test at the 10% level. This leads us to the conclusion that the technical efficiency of the target firm is not a significant determinant of the abnormal return for the stockholders of acquiring firms. In the same equation, the size of the target firm (Size2) is found to be statistically insignificant at the 10% level in the OLS regression. By contrast, it is found to be significantly different from 0 at the 10% level in a 2-tailed test and significantly positive at the 5% level in a 1-tailed test in the bootstrap regression. In the regression for the target firms, Phi2 is the only variable that is significantly different from 0 in the OLS regression. In the bootstrap regression, apart from Phi2, Phi1 is significantly positive at the 5% level and the payment method (PM) is also positive at 7.5% level in one-tailed tests.

It may be noted that the coefficient of Phi1 is significantly positive in both regressions. This implies that the abnormal return is higher for the bidder if the firm is

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[23] If the coefficient is positive, empirical p-value measures the percentage of the bootstrap replications that are negative, and vice versa.

less efficient before merger because the merger activity is interpreted as an effort to improve efficiency and thereby to increase the future income flows. In the context of the target, this sign is a little bit puzzling. One plausible explanation can be that target firms might have a superior bargaining position towards a low efficient bidder, thus make the target firms attractive in the market. The coefficient for Phi2 is not significant to the acquirers, which implies that the investors of acquirers in general do not consider the efficiency level of the target firms. However, the market reactions towards inefficient targets from the point of view of the stockholders of the acquired firms are not the same as the acquiring firms. As can be seen, the coefficient of Phi2 in regression for targets is significantly positive. This reflects that the fact that the market is in favor of eliminating an inefficient firm and its management. Therefore, market views the merger as beneficial for the investors of the targets. As expected the coefficient for the payment method is significantly positive in both regressions, which reflects that the market favors the payment in cash. Such cash payment can be regarded either as a sign of the financial strengthen of the acquiring firm, or as a signal of reducing the free extra cash holding of the acquiring firms (Jensen, 1986). It can also be found that the coefficient of concentration ratio is not significant in either of the regressions, which is consistent with the findings of Eckbo (1985). It may imply that firms in manufacturing industry usually do not consider monopolizing the market as the primary benefit through horizontal mergers; instead they care more about the improvement of their fundamental performance. On the other hand, an increase in the size of the target lowers the abnormal return of the acquiring firm. When a large firm is acquired, it usually requires major restructuring before the economic performance can be improved.

The overall results can be summarized as follows:

- Lower efficiency of an acquirer has a positive impact on the abnormal returns of both participating firms;

- Lower efficiency of the target has positive impact only on the value of the target firm;

- The market favors cash payment for the acquisition;

- An increase in the size of the target has a negative impact on the acquirer's abnormal returns;

- Market concentration plays an insignificant role in horizontal mergers in manufacturing industries.

5. Conclusions

Technical inefficiency, as measured by DEA, captures a firm's shortfall from the maximum output producible from a given mount of inputs. Abnormal returns of an event reflect the investor's re-evaluation of the future performance potential of the participating firms. We find that there is a significant relationship between technical efficiency and market response. The market apparently welcomes the merger as a beneficial arrangement to better utilize the productive resources.

Table 1: Stock Return at One-month Interval around the Event Date

Time	AAR_bidders	t-ratio	CAR_bidders	AAR_targets	t-ratio	CAR_targets
-15	-0.001651	-0.542145	-0.001651	0.003753	0.701198	0.003753
-14	0.000124	0.040637	-0.001528	0.000931	0.173869	0.004684
-13	0.001544	0.506798	0.000016	0.000914	0.170757	0.005598
-12	-0.004325	-1.419957	-0.004309	0.003027	0.565604	0.008625
-11	0.003444	1.130621	-0.000865	0.010458	1.953946	0.019084
-10	-0.002078	-0.682249	-0.002943	0.005556	1.038010	0.024640
-9	0.003670	1.204842	0.000727	0.007142	1.334369	0.031782
-8	0.003745	1.229507	0.004472	0.006064	1.132981	0.037846
-7	-0.003262	-1.070806	0.001210	0.004847	0.905605	0.042693
-6	0.005285	1.735183	0.006495	0.005521	1.031506	0.048214
-5	0.004985	1.636631	0.011480	0.012732	2.378632	0.060946
-4	0.004392	1.441908	0.015872	0.014076	2.629853	0.075022
-3	0.007498	2.461722	0.023370	0.015280	2.854675	0.090302
-2	-0.003975	-1.304950	0.019396	0.009049	1.690599	0.099351
-1	0.000082	0.026983	0.019478	0.011397	2.129248	0.110748
0	-0.013387	-4.395027	0.006091	0.193612	36.172209	0.304359
1	-0.000277	-0.091020	0.005814	0.060859	11.370120	0.365218
2	-0.003271	-1.073850	0.002543	0.004291	0.801626	0.369509
3	0.000116	0.038126	0.002659	-0.004100	-0.766063	0.365408
4	-0.000502	-0.164846	0.002157	0.002607	0.487027	0.368015
5	0.001047	0.343770	0.003204	-0.001698	-0.317302	0.366317
6	0.004219	1.385167	0.007423	0.005200	0.971435	0.371516
7	0.001113	0.365246	0.008536	-0.001970	-0.368091	0.369546
8	0.000233	0.076401	0.008768	0.000020	0.003662	0.369566
9	0.001108	0.363927	0.009877	0.001449	0.270651	0.371014
10	0.000410	0.134550	0.010287	-0.001055	-0.197077	0.369960
11	-0.000457	-0.150161	0.009829	0.002788	0.520934	0.372748
12	-0.000426	-0.139929	0.009403	0.000887	0.165809	0.373635
13	-0.002157	-0.708272	0.007246	-0.001928	-0.360215	0.371707
14	0.000447	0.146824	0.007693	-0.000480	-0.089619	0.371228
15	-0.004561	-1.497399	0.003132	0.002552	0.476694	0.373779

AAR: average abnormal returns
CAR: cumulative abnormal returns

Table 2: Summary Statistics of the Regression Data

Description	Mean	Standard error
Dependent variables:		
Cumulative abnormal return for acquirers (CAR_acq)	-0.01358	0.08056
Cumulative abnormal return for targets (CAR_tag)	0.26587	0.24441
Explanatory variables:		
Technical inefficiency for acquirers (Phi1)	1.3548	1.0131
Technical inefficiency for target firms (Phi2)	1.5892	0.9983
Method of Payment (PM)	0.425	0.4974
Industry concentration ratio (CR)	0.5034	0.1188
Logarithm of the size of the acquirers (Log(Size1))	6.8456	1.7281
Logarithm of the size of the targets (Log(Size2))	4.5958	1.4560
Total number of the observations: 80		

Table 3: Cross Sectional OLS Regression for Bidders and Targets

F statistic: 6.23* R^2: 0.3386 N=80 Dependent Variable: CAR_acq

Parameters	estimates	standard error	t statistics
Intercept	-0.14282*	0.05150	-2.77
Phi1	0.04507*	0.00833	5.41
Phi2	-0.01733*	0.00839	-2.07
PM	0.03479*	0.01600	2.17
CR	0.07673	0.06672	1.15
Log(Size1)	0.01261*	0.00536	2.35
Log(Size2)	-0.00958	0.00637	-1.50

F statistic: 1.80 R^2: 0.1286 N =80 Dependent Variable: CAR_tag

Parameters	estimates	standard error	t statistics
Intercept	-0.08395	0.17935	-0.47
Phi1	0.04041	0.02901	1.39
Phi2	0.05282**	0.02922	1.81
PM	0.07766	0.05572	1.39
CR	-0.08584	0.23237	-0.37
Log(Size1)	0.01605	0.01865	0.86
Log(Size2)	0.02425	0.02218	1.09

Notes: * represents 5% significance level for two-tailed 't' test; ** represent 10% significance level for two-tailed 't' test.

Table 4: Test Results for Normality and Heteroskedasticity

Residuals of the regression for the bidders:

Test name	Test statistics	P value
Test for normality		
Shapiro-Wilk	0.963672	0.0226
Kolmogorov-Smirnov	0.078313	0.1500
Cramer-von Mises	0.115144	0.0730
Anderson-Darling	0.806789	0.0371
Bera-Jarque	5.4294	0.0662
Test against heteroskedasticity		
White test	41.4	0.0283

Residuals of the regression for the acquirers:

Test name	Test Statistics	P value
Test for normality		
Shapiro-Wilk	0.9161	0.0001
Kolmogorov-Smirnov	0.1045	0.0297
Cramer-von Mises	0.1847	0.0083
Anderson-Darling	1.2479	0.0050
Bera-Jarque	8.5356	0.0000
Test against heteroskedasticity		
White test	50.62	0.0026

Notes:
Shapiro-Wilk test: a test for normality based on the linear combination of order statistics.
Kolmogorov-Smirnov: a goodness-of-fit test for normality based on the empirical distribution and it measures the maximum vertical distance between empirical distribution and normal CDF.
Anderson-Darling: a goodness-of-fit test for normality based on the empirical distribution and it is based on squared differences between empirical distribution and normal CDF using a different weights.
Cramer-von Mises: a goodness-of-fit test for normality based on the empirical distribution and it is based on squared difference between empirical distribution and normal CDF with unitary weight.
Jarque-Bera: A test for normal distribution with unspecified mean and variance. The test statistic is based on the estimates of the sample skewness and kurtosis.
White: White general test for heteroskedasticity.

Table 5: Wild Bootstrap Estimation for Bidders

Parameters	Estimate	Standard errors	Percentile Estimation			
			2.50%	5%	95%	97.50%
Intercept	-0.1445*	0.0563	-0.2472	-0.2351	-0.0487	-0.0317
Phi1	0.0451*	0.0082	0.0284	0.0301	0.0553	0.0566
Phi2	-0.0170	0.0131	-0.0405	-0.0388	0.0061	0.0074
PM	0.0346*	0.0153	0.0033	0.0089	0.0590	0.0637
CR	0.0775	0.0636	-0.0466	-0.0266	0.1830	0.2006
Size1	0.0127*	0.0051	0.0022	0.0038	0.0208	0.0225
Size2	-0.0094**	0.0059	-0.0217	-0.0198	-0.0003	0.0013

OLS Estimation for Bidders

Parameters	Estimate	Standard errors	95% CI		90% CI	
Intercept	-0.1428*	0.0515	-0.2286	-0.0570	-0.2455	-0.0402
Phi1	0.0451*	0.0083	0.0312	0.0590	0.0285	0.0617
Phi2	-0.0173*	0.0084	-0.0313	-0.0034	-0.0340	-0.0006
PM	0.0348*	0.0160	0.0081	0.0614	0.0029	0.0667
CR	0.0767	0.0667	-0.0344	0.1879	-0.0562	0.2097
Size1	0.0126*	0.0053	0.0037	0.0215	0.0019	0.0233
Size2	-0.0096	0.0064	-0.0202	0.0010	-0.0223	0.0031

Wild Bootstrap for Bidders

Parameters	Estimate	Standard errors	One-sided p-value
Intercept	-0.1445*	0.0563	**0.0065**
Phi1	0.0451*	0.0082	**0**
Phi2	-0.0170	0.0131	**0.169**
PM	0.0346*	0.0153	**0.0145**
CR	0.0775***	0.0636	**0.1095**
Size1	0.0127*	0.0051	**0.0065**
Size2	-0.0094*	0.0059	**0.0455**

Notes: * represents 5% two-tailed significance; ** represent 10% two-tailed significance; *** represents 10% one-tailed significance.
One-sided P-value is calculated as: (# of positive or negative replications/ all the bootstrap replications).

Table 6: Wild Bootstrap Estimation for Target

Parameters	Estimates	Standard error	Percentile estimation			
			2.50%	5%	95%	97.50%
Intercept	-0.0899	0.1554	-0.4094	-0.3612	0.1657	0.2014
Phi1	0.0409*	0.0095	0.0217	0.0249	0.0563	0.0592
Phi2	0.0535**	0.0308	-0.0092	0.0004	0.1032	0.1109
PM	0.0794	0.0528	-0.0281	-0.0122	0.1633	0.1781
CR	-0.0886	0.1993	-0.4488	-0.3923	0.2730	0.3362
Size1	0.0161	0.0215	-0.0248	-0.0173	0.0525	0.0581
Size2	0.0251	0.0255	-0.0279	-0.0179	0.0685	0.0758

OLS Estimation for Target

Parameters	Estimates	Standard error	90% CI		95% CI	
Intercept	-0.0840	0.1794	-0.3827	0.2148	-0.4414	0.2735
Phi1	0.0404	0.0290	-0.0079	0.0887	-0.0174	0.0982
Phi2	0.0528**	0.0292	0.0041	0.1015	-0.0054	0.1111
PM	0.0777	0.0557	-0.0152	0.1706	-0.0334	0.1887
CR	-0.0858	0.2324	-0.4730	0.3013	-0.5490	0.3773
Size1	0.0161	0.0187	-0.0150	0.0471	-0.0211	0.0532
Size2	0.0243	0.0222	-0.0127	0.0612	-0.0200	0.0685

Wild Bootstrap for Target

Parameters	Estimates	Standard error	One-sided p-value
Intercept	-0.0899	0.1554	**0.2960**
Phi1	0.0409*	0.0095	**0.0000**
Phi2	0.0535**	0.0308	**0.0485**
PM	0.0794***	0.0528	**0.0720**
CR	-0.0886	0.1993	**0.3465**
Size1	0.0161	0.0215	**0.2495**
Size2	0.0251	0.0255	**0.1805**

Notes: * represents 5% two-tailed significance; ** represent 10% two-tailed significance; *** represents 10% one-tailed significance.

One-sided P-value is calculated as: (# of positive or negative replications/ all the bootstrap replications).
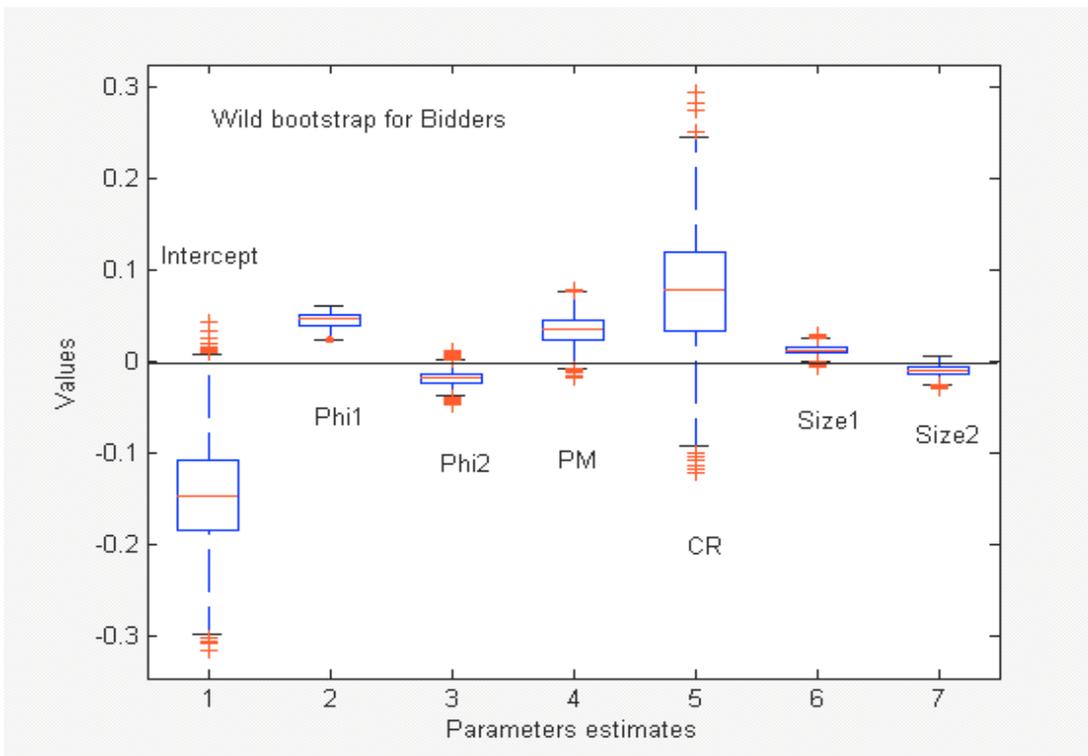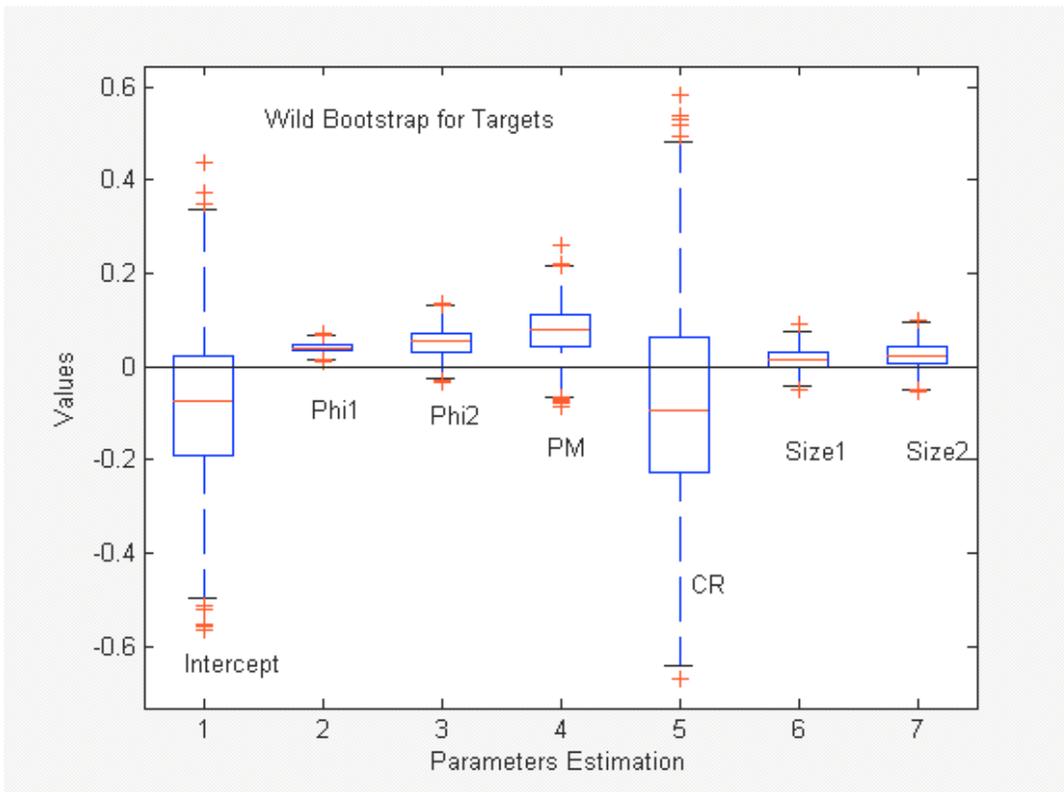
Figure 2. Boxplots of regression parameters using wild bootstrap method

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