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Market-based Valuation Multiples: Evidence from Agribusiness Sector

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ABSTRACT

This article investigates the choice of multiples in valuing the agribusiness firms in Malaysia from 2003 to 2009. The agribusiness industry typically employs homogenous business models and produces standardized products, thus rendering excellent empirical settings to reveal the value drivers of such traditional industries. It was discovered that commonly adopted methodologies in valuation multiples are associated with pitfalls which may hamper the reliability of the valuations. Our findings also showed that price-to-earnings multiple leads to the best valuation performance, while price-to-sales multiple produces the worst results. Moreover, this research showed that growth prospect is an effective control factor in multiples valuation.

Keywords: Agribusiness, plantation, corporate valuation, multiples, value driver

INTRODUCTION

In corporate valuation, academicians tend to favour Discounted Cash Flow (DCF) model, which is based on the intrinsic value concept over multiples as academic researchers and educationists have strong preferences in the fundamental valuation over accrual based valuation (Kaplan & Ruback, 1995; Imam & Shah, 2013). Nonetheless, multiples still have distinct advantages since it can be used to reflect market perception, to identify over-price

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Early works on valuation multiples have shown that there is a direct correlation between expected earnings per share and price-to-earnings multiples (Hammel & Hodes, 1967; Michaud, 1990). However, there are limits to how far the price-toearnings can be used as the predictor of future earnings growth (Murphy & Stevenson, 1967). One major criticism of the literature on valuation multiples is that prior studies have failed to reach a conclusive evidence concerning the choice of suitable benchmark multiples, i.e., comparable firms and statistical methods (Lie & Lie, 2002). In recent years, there has been an increasing amount of literature to investigate how to increase the prediction accuracy of valuation multiples. Most studies, however, are concentrated in advanced economies (e.g., Cheng & McNamara, 2000; Lie & Lie, 2002; Herrmann & Richter, 2003; Park & Lee, 2003; Dittmann & Weiner, 2005; Schreiner & Spremann, 2007; Fidanza, 2008). On the contrary, there is only one related study focusing on the emerging economies (Mînjina, 2009).

Evidently, there has been little discussion about selecting comparable firms in emerging economies. As a result, analysts often rely on the definition of comparable firms based on advanced economies when using valuation multiples in the contexts of emerging economies (Ivashkovskaya & Kuznetsov, 2007). Such approach has recently been challenged by Ivashkovskaya and Kuznetsov (2007) who showed that the prediction accuracy of multiples is significantly higher in the United States compared to Russia after the country risks have been corrected. Furthermore, the valuation accuracy of multiples tends to increase by using the

price-to-book and enterprise value-to-sales multiples. Surprisingly, price-to-earnings multiple delivers worst valuation accuracy. Our preliminary conclusion is that the performance of valuation multiples in emerging economies may differ from advanced economies.

Despite the fact that there is insufficient knowledge on using multiples in corporate valuation, multiples are still commonly used in equity valuation and pricing for initial public offering firms (Damodaran, 2005; Roosenboom, 2012). For instance, Japanese analysts generally prefer multiples for the ease and simplicity of corporate valuation compared to Discounted Cash Flow (DCF) model (Park & Lee, 2003). However, one should note that multiples are difficult to be implemented correctly because practitioners rely on subjective decisions to select comparable firms (Damodaran, 2005). Furthermore, the criteria to select comparable firms are difficult to be identified because each firm faces different business challenges and some have few revenue (or negative earnings). Many practitioners also lack good knowledge about the value driver of multiples, the methodology in choosing comparable firms and the defectiveness of traditional valuation multiples (Schreiner & Spremann; 2007).

Likewise, researchers in the area of corporate valuation consistently note that most of the literatures fail to provide a comprehensive framework to guide practitioners on how to use multiples effectively (e.g., Kim & Ritter, 1999; Bhojraj & Lee, 2001; Liu et al., 2001;

Lie & Lie, 2002; Hermann & Richter, 2003; Dittman & Weiner, 2005; Schreiner & Spremann, 2007). In more specific, Schreiner and Spremann (2007) highlighted that future studies should consider the empirical setting of emerging markets to offer insights of valuation multiples. Thus, the aim of this article is to formulate a comprehensive methodology in valuation multiples in emerging economies. This study also considers the importance of industrial setting in valuation multiples. In particular, we chose agribusiness firms from Malaysia on the understanding that agribusiness sector is unique due to its homogenous business model in producing standardized commodity products.

RESEARCH DESIGN

In this study, we intended to formulate comprehensive methodologies of multiples in corporate valuation to predict the market performance of Malaysian agribusiness firms. In this regard, the valuation accuracy of multiples relies on two important processes; estimate benchmark multiple and identify value drivers. First, the guideline in specifying comparable firms is paramount to obtain a reliable benchmark multiple. Second, the performance measure (or valuation accuracy) of multiples needs to be examined to identify the relative performance of multiples and the value driver of agribusiness firms.

Estimating the Benchmark Multiple

There are three approaches that are relevant to the estimating the benchmark

multiple in corporate valuation. The first utilizes the fundamental variables of DCF model, the second derived from multiple linear regression, and the third focuses on theoretical concepts of comparable firms.

The first approach in valuation multiples is to associate the multiples with fundamental variables in DCF model such as risk, expected growth rate and cash flow generating capacity (Damodaran, 2005). For example, an analyst can combine Gordon Growth Model (GGM) and Dividend Discount Model (DDM) to estimate the market value of equity, i.e., Stock Price = Expected Dividend / (Discount Rate - Growth Rate). The analyst can then integrate the estimated stock price with the actual value of the denominator (e.g., earnings for price-to-earnings multiple) to generate his own 'justified multiple' (or benchmark multiple). Then, the 'justified multiple' is compared with actual multiple to justify if the current stock price is overor undervalued. However, this approach is exposed to similar weakness in DCF model, i.e., its sensitivity to the assumptions (Damodaran, 2005; Schreiner & Spremann, 2007). Another major disadvantage of such method is that the 'justified multiple' is assumed to be linearly proportional to the value driver (or denominator), and thus, it may not be unreasonable in practice (Schreiner & Spremann, 2007).

While the first approach relies almost exclusively on GGM and DDM models, the second approach utilizes multiple linear regression to estimate benchmark multiples. This technique estimates benchmark

multiple through the regression analysis between the market variable of multiple (i.e., dependent variable) and fundamental based variables such as growth, payout ratio and risk as independent variables (Bhojraj & Lee, 2001; Damodaran, 2005). The advantage of this approach is that it examines a cross-sectional effect of fundamental variables which is based upon actual data. Nonetheless, Damodaran (2005) found that regression approach fails to produce reliable and accurate benchmark multiples. The rationale for this is that the intercept and coefficient of variables and R-square (i.e., explanatory power) in the regression model fluctuate widely over time. The most likely causes of noisy benchmark multiples are the business cycle fluctuations and regression shortcomings such as multicollinearity issue and non-normally distributed samples. A similar empirical result was also discovered by Hermann and Richter (2003) whereby the findings indicate that the benchmark multiples derived from regression models generate higher valuation errors compared to the one using statistical estimator.

The third approach of selecting the benchmark multiple relies on theoretical concepts that assume comparable firms have identical fundamentals such as risk, growth and cash flow generating capacity; and hence the same benchmark multiple is produced within a certain period (Damodaran, 2005; Schreiner & Spremann, 2007). Traditionally, analysts view an average of multiples from the comparable firms to be a good proxy of benchmark multiple. The underlying assumption is that comparable

firms will have identical fundamentals. The performance of this approach relies on to what extent the fundamentals of comparable firms are identical to studied firms.

Clearly, the aforementioned discussions show that we have insufficient competence to estimate a benchmark multiple in valuation multiples. Our fundamental view is that using theoretical concepts to identify comparable firms with identical fundamentals is most appropriate to estimate benchmark multiple. This can be explained by the fact that the cross-sectional effect of the fundamentals will become closer in the fine-grained comparable firms. Furthermore, we believe comparable firms with identical fundamentals are commonly found in the agribusiness industry. The reason is that the agribusiness industry, unlike many other industries, does not require sophisticated production technologies and high R&D activities in business model.

To reiterate our point, we propose that a fine-grained comparable firm is sufficient in valuation multiples. However, to the best of our knowledge, there has been no discussion about how to choose the optimal number of comparable firms (Dittman & Weiner, 2005). In order to address the problem, two selection methods are adopted to select comparable firms. First, the traditional approach whereby the industry membership is used to select the comparable firm to estimate benchmark multiples. Second, the comparable firms are controlled based on proxy of growth in the same industry. In this context, return on equity (ROE) is the proxy of growth since the increase

of ROE leads to higher growth rate and vice versa (Damodaran, 2006). In more specific, we classified comparable firms into four groups which are: the average ROE of the firm is less than 5% as the first group; firms' average ROE is greater than 5% but less than 10% as the second group; firms' average ROE is more than 10% but less than 15% as the third group; the firms' average ROE is greater than 15% as the last group. This classification will produce better comparable firms based on the profitability growth rate.

Selecting Statistical Estimator for Benchmark Multiple

Recent studies of valuation multiples have clearly demonstrated that the paradox in selecting statistical estimator for benchmark multiple. In general, median and the harmonic mean are widely accepted statistical estimators to calculate the benchmark multiple. The arithmetic mean is ruled out because it tends to overestimate benchmark multiple when the multiple distributions are asymmetric (Hermann & Richter 2003).

To date, harmonic means is one of commonly used statistical estimators to calculate the benchmark multiple of comparable firms. Prior studies have shown that using harmonic mean to estimate benchmark multiple produces best valuation performance for multiples (Baker & Ruback, 1999; Liu *et al.*, 2001). One similarity in the prior studies is that the outlier of multiples is mitigated prior to the analysis. Following the previous studies, Mînjina

(2009) removed the extreme multiples' values which are less than 1 percentile and greater than 99 percentiles of the multiple distributions prior to valuation multiples. However, the exclusion of the extreme multiples signifies the newly improved data may cause biased selection and pose a threat to reliability of the result. Indeed, Hermann and Richter (2003) found that harmonic mean is the worst statistical estimator for benchmark multiple when outlier effect is not eliminated, while in contrast, the median is found to be the most accurate statistical estimator in heterogeneous samples.

In addition, we believe that the harmonic mean may be a superior statistical estimator by chance when the outliers of multiple distributions are not mitigated. The rationale is that the statistical estimator may produce best valuation accuracy based on the shape of sample distribution. Imagine that if the sample distribution is skewed to the left; hence, "mean < median < mode". This implies that "harmonic mean \leq mean \leq median < mode" since the harmonic mean cannot be larger than the arithmetic mean. In contrast, if the distribution is skewed to the right; hence, "mean > median > mode". Arguably, it denotes that "mean > median > mode" and "mean > harmonic mean". In this scenario, median and the harmonic mean are closer to each other in the distribution, which is skewed to the right. Therefore, harmonic mean and median will perform very close to each other in valuation multiples. Furthermore, it is perfectly possible that valuation errors distribution may affect the effectiveness of harmonic mean as a statistical estimator for benchmark multiple. For example, Liu *et al.* (2001) found that using harmonic mean to estimate benchmark multiples produce smaller valuation errors compared to those using arithmetic mean and median. However, they explained that valuation errors in their study are skewed to the left; thereby the arithmetic mean is smaller than the median. This denotes that the harmonic means is probably a better statistical estimator for benchmark multiple in left-skewed valuation errors distribution.

The above discussion shows that harmonic mean is likely to be a better statistical estimator for benchmark multiple when the following conditions are fulfilled: (i) distribution of valuation errors is leftskewed; and (ii) the outlier of multiple distributions is mitigated. Notably, prior studies have also favored the median as the statistical estimator for benchmark multiple (e.g., Alford, 1992; Cheng &McNamara, 2000; Lie & Lie, 2002; Park & Lee, 2003; Schreiner & Spremann, 2007). Alford (1992) argued that using the median as a statistical estimator can mitigate outlier effect that ascribe to extreme multiples. The study by Lie and Lie (2002) also supports the argument, i.e., using medians as statistical estimator for benchmark multiple does not produce biased estimation while arithmetic means is sensitive to the extreme outlier. Given the fact that prior studies provide inconclusive evidence in the selection of reliable statistical estimator for benchmark multiple (Baker & Ruback, 1999; Liu et al., 2001; Hermann & Richter, 2003), the median is chosen as the statistical estimator

for benchmark multiple because we do not intend to eliminate any of the outlier in the samples.

Performance Measure for Multiples

Multiple is defined as a ratio of a market price variable to its value driver (Schreiner & Spremann, 2007). The underlying concept of value driver (i.e., the denominator) for a multiple is interpreted as a determinant of equity price (i.e., the numerator). In this context, we could expect value drivers to affect the market price differently and thus to be reflected in valuation accuracy of the multiples. As such, we can rank the valuation performance of multiples based on valuation errors, and the results can be used as a guideline in selecting the best performed multiple in corporate valuation. For example, if the valuation accuracy of price-to-earnings were found to be smaller than the one of price-to-sales, we can infer that earnings are a more significant value driver and vice versa.

In corporate valuation, prior studies have reached a consensus to estimate the predicted stock price using benchmark multiple based on theoretical concepts of multiples (e.g., Alford, 1992; Cheng & McNamara, 2000; Liu et al., 2001; Lie & Lie, 2002; Schreiner & Spremann, 2007; Mînjina, 2009). That is, the predicted stock price is a product of a value driver of a firm (i.e., the denominator of multiple) and benchmark multiple as shown in equation [1]. This approach, which requires fewer assumptions, is more appropriate compared to other approaches, particularly regression

that is sensitive to violation of assumptions in estimation (Alford, 1992).

$$\Pi_{i,t} = D_{i,t} * M_{i,t}$$

Predicted stock (or firm) price and denominator of multiple are represented by $\Pi_{i,t}$ and $D_{i,t}$ at year (or period) "t". The benchmark multiple for firm "i" is indicated $M_{i,t}$. As a linear relationship is likely invalid between actual- and predicted price, valuation errors will exist as shown in equation (2), as proposed by Liu *et al.* (2001) and Schreiner and Spremann (2007). The $\epsilon_{i,t}$ represents the valuation errors of firm 'i' at year (or period) 't' and $\pi_{i,t}$ is the actual price.

$$\pi_{i,t} = \prod_{i,t} + \varepsilon_{i,t} \tag{2}$$

In order to estimate the relative performance of multiples, the valuation errors are required to be scaled with stock price to control the size effects (Cheng & McNamara, 2000). The purpose of scaling is to standardize valuation errors and thus can be compared in percentage terms rather than magnitude. Unfortunately, there is no consensus in literature to select the scaling factor. On the one hand, Mînjina (2009), Schreiner and Spremann (2007) and Liu et al. (2001) chose the actual price as the scaling factor since it is consistent with prior research by Alford (1992). On the other hand, Park and Lee (2003) and Cheng and McNamara (2000) adopted predicted price as the scale factor as it renders consistency in valuation errors. To illustrate this, assume that the under-predicted price and overpredicted price have equivalent distance from benchmark price, scaling of nonbenchmark price (i.e., actual price) will make scaled absolute valuation error to differ in magnitude. In contrast, scaling by the predicted prices will eliminate this problem. Thus, the predicted price is adopted as a scaling factor in this study. As we are only interested in the magnitude of valuation errors, the scaled valuation errors are transformed into the equation [3].

$$|\epsilon_{i,t}/\Pi_{i,t}| = [(\pi_{i,t} - \Pi_{i,t})/\Pi_{i,t}]$$
 [3]

Lastly, we need to select the statistical estimator of valuation errors to identify which multiple is more superior in terms of valuation performance (Hermann & Richter, 2003). The median is used in this study as it is a more robust statistical estimator for highly skewed data, whilst being less sensitive to extreme outliers (Norman & Streiner, 2007). In other words, the performance measure of multiples is based on median absolute error (MeAE) whereby lower MeAE implies higher valuation accuracy for multiples.

To assess the reliability of performance measure, the Wilcoxon Rank Sum test is used to distinguish the relative performance of multiples. Wilcoxon rank sum test is a non-parametric test that does not require normally distributed data. The null hypothesis in the Wilcoxon rank sum test assumes that two independent samples have the same shape of data distribution (Russo, 2003). The purpose of the null hypothesis is

to identify if two comparable groups have the same central tendencies (i.e., the median used in this study). If the null hypothesis is not true, it signifies two comparable groups have different medians. Then, the Wilcoxon rank sum test statistic can be used to identify which group of data is systematically larger (or statistically superior) than the other group (Moore & McCabe, 2005).

DATASET

In this study, the "Plantation Index" in Bursa Malaysia is used as the basis for identifying agribusiness firms. There are 41 firms listed in the Plantation Index. The dataset consists of the multiples for firms over seven annual periods from 2003 to 2009. In order to construct the multiples, the market equity price and financial data are required. The equity price is collected from Bursa Station database, whereas the financial and outstanding shares data are obtained from the annual reports. After excluding the missing data, there are 260 firm-year observations in this dataset.

The multiples are calculated according to the following steps. First, we need to estimate the value of equity (or the numerator) of multiples, i.e., market capitalization. The market capitalization is a product of the outstanding shares and share price. The data about outstanding shares of firms are extracted from the annual reports. The equity price is taken from the closing price of the last trading day in the month of the financial calendar. Thus, we can match the equity price and number of shares at the particular point of the time precisely

and it is not affected by stock split. Second, we need to estimate the value drivers (or the denominator) of multiples. The value drivers such as total revenue, earnings, book value of equity and asset are obtained from financial statements in annual reports. Specifically, we calculate the proxy of cash flow as the summation of net income, depreciation and amortization in financial statements (Park & Lee, 2003). Finally, we removed negative price-to-earnings and price-to-cash flow multiples since they are meaningless and cannot be interpreted.

Damodaran (2006) suggested that 'Descriptional Tests' such as average, median, standard deviation, standard error, minimum and maximum are necessary in valuation multiples to understand the characteristics of multiple distributions prior to analysis. Nonetheless, we believe that it is more appropriate to present the dataset with the inter-quartile range. The rationale for this is that investment analysts are generally more interested in middle concentration of distributions that are less affected by outliers. Additionally, the standard deviation and standard error are generally useful provided that the sample data are normally distributed. Such normally distributed data, however, are rarely exist in real valuation context. Table 1 shows the means, median and inter-quartile of multiples and return on equity (ROE) for multiple dataset. All multiple distributions are skewed to the right since the mean is greater than the median. The distribution of ROE was also skewed to the right in 2003, but the distributions of ROE were skewed

Table 1
Descriptive Statistics of Multiples and ROE

Descriptive	Year						
Multiple Statistics	2003	2004	2005	2006	2007	2008	2009
Mean	12.48	11.76	14.21	17.69	20.94	6.73	17.98
Median	10.54	9.62	11.00	13.53	10.82	6.03	10.98
IQR	7.48	6.83	8.72	7.12	3.66	3.98	5.25
	30	30	28	33	38	37	35
Mean	0.83	0.82	0.74	1.06	1.55	1.15	1.23
Median	0.67	0.71	0.68	0.77	1.24	0.73	0.90
IQR	0.65	0.47	0.51	0.60	0.82	0.67	0.69
	34	34	33	37	40	40	41
Mean	11.88	9.05	12.06	12.23	13.35	8.63	31.39
Median	8.49	7.55	8.63	10.65	8.88	5.61	8.94
IQR	8.12	6.67	5.03	6.68	3.70	3.19	7.45
	31	31	29	35	39	38	37
Mean	9.13	9.98	8.06	3.95	4.69	2.60	4.43
Median	2.18	1.72	1.70	2.49	3.23	1.31	2.38
IQR	3.31	3.39	3.83	3.01	3.07	2.36	3.98
	35	35	34	37	39	39	40
Mean	0.64	0.63	0.57	0.71	1.08	0.78	0.85
Median	0.47	0.51	0.47	0.62	0.91	0.58	0.62
IQR	0.57	0.42	0.50	0.52	0.75	0.50	0.65
	34	34	33	37	40	40	41
Mean	7.11%	7.34%	4.40%	0.80%	6.77%	5.66%	7.62%
Median	6.53%	7.59%	5.35%	5.12%	13.29%	12.10%	7.93%
IQR	6.27%	5.76%	5.76%	7.02%	9.16%	11.16%	5.06%
	34	34	33	37	40	40	41
	Mean Median IQR Mean Median IQR	Statistics 2003 Mean 12.48 Median 10.54 IQR 7.48 30 Mean Median 0.67 IQR 0.65 34 Mean Median 8.49 IQR 8.12 31 Mean Median 2.18 IQR 3.31 Mean 0.64 Median 0.47 IQR 0.57 Mean 7.11% Median 6.53% IQR 6.27%	Statistics 2003 2004 Mean 12.48 11.76 Median 10.54 9.62 IQR 7.48 6.83 30 30 Mean 0.83 0.82 Median 0.67 0.71 IQR 0.65 0.47 Mean 11.88 9.05 Median 8.49 7.55 IQR 8.12 6.67 31 31 31 Mean 9.13 9.98 Median 2.18 1.72 IQR 3.31 3.39 Median 0.64 0.63 Median 0.47 0.51 IQR 0.57 0.42 34 34 Mean 7.11% 7.34% Median 6.53% 7.59% IQR 6.27% 5.76%	Statistics 2003 2004 2005 Mean 12.48 11.76 14.21 Median 10.54 9.62 11.00 IQR 7.48 6.83 8.72 30 30 28 Mean 0.83 0.82 0.74 Median 0.67 0.71 0.68 IQR 0.65 0.47 0.51 Mean 11.88 9.05 12.06 Median 8.49 7.55 8.63 IQR 8.12 6.67 5.03 Mean 9.13 9.98 8.06 Median 2.18 1.72 1.70 IQR 3.31 3.39 3.83 Mean 0.64 0.63 0.57 Median 0.47 0.51 0.47 IQR 0.57 0.42 0.50 Median 7.11% 7.34% 4.40% Mean 7.11% 7.59% 5.35%	Statistics 2003 2004 2005 2006 Mean 12.48 11.76 14.21 17.69 Median 10.54 9.62 11.00 13.53 IQR 7.48 6.83 8.72 7.12 30 30 28 33 Mean 0.83 0.82 0.74 1.06 Median 0.67 0.71 0.68 0.77 IQR 0.65 0.47 0.51 0.60 34 34 33 37 Mean 11.88 9.05 12.06 12.23 Median 8.49 7.55 8.63 10.65 IQR 8.12 6.67 5.03 6.68 Mean 9.13 9.98 8.06 3.95 Median 2.18 1.72 1.70 2.49 IQR 3.31 3.39 3.83 3.01 Mean 0.64 0.63 0.57 0.71 <t< td=""><td>Statistics 2003 2004 2005 2006 2007 Mean 12.48 11.76 14.21 17.69 20.94 Median 10.54 9.62 11.00 13.53 10.82 IQR 7.48 6.83 8.72 7.12 3.66 30 30 28 33 38 Mean 0.83 0.82 0.74 1.06 1.55 Median 0.67 0.71 0.68 0.77 1.24 IQR 0.65 0.47 0.51 0.60 0.82 Mean 11.88 9.05 12.06 12.23 13.35 Median 8.49 7.55 8.63 10.65 8.88 IQR 8.12 6.67 5.03 6.68 3.70 Mean 9.13 9.98 8.06 3.95 4.69 Median 2.18 1.72 1.70 2.49 3.23 IQR 3.31 3.39 3.</td><td>Statistics 2003 2004 2005 2006 2007 2008 Mean 12.48 11.76 14.21 17.69 20.94 6.73 Median 10.54 9.62 11.00 13.53 10.82 6.03 IQR 7.48 6.83 8.72 7.12 3.66 3.98 Mean 0.83 0.82 0.74 1.06 1.55 1.15 Median 0.67 0.71 0.68 0.77 1.24 0.73 IQR 0.65 0.47 0.51 0.60 0.82 0.67 Mean 11.88 9.05 12.06 12.23 13.35 8.63 Median 8.49 7.55 8.63 10.65 8.88 5.61 IQR 8.12 6.67 5.03 6.68 3.70 3.19 Mean 9.13 9.98 8.06 3.95 4.69 2.60 Median 2.18 1.72 1.70 2.49</td></t<>	Statistics 2003 2004 2005 2006 2007 Mean 12.48 11.76 14.21 17.69 20.94 Median 10.54 9.62 11.00 13.53 10.82 IQR 7.48 6.83 8.72 7.12 3.66 30 30 28 33 38 Mean 0.83 0.82 0.74 1.06 1.55 Median 0.67 0.71 0.68 0.77 1.24 IQR 0.65 0.47 0.51 0.60 0.82 Mean 11.88 9.05 12.06 12.23 13.35 Median 8.49 7.55 8.63 10.65 8.88 IQR 8.12 6.67 5.03 6.68 3.70 Mean 9.13 9.98 8.06 3.95 4.69 Median 2.18 1.72 1.70 2.49 3.23 IQR 3.31 3.39 3.	Statistics 2003 2004 2005 2006 2007 2008 Mean 12.48 11.76 14.21 17.69 20.94 6.73 Median 10.54 9.62 11.00 13.53 10.82 6.03 IQR 7.48 6.83 8.72 7.12 3.66 3.98 Mean 0.83 0.82 0.74 1.06 1.55 1.15 Median 0.67 0.71 0.68 0.77 1.24 0.73 IQR 0.65 0.47 0.51 0.60 0.82 0.67 Mean 11.88 9.05 12.06 12.23 13.35 8.63 Median 8.49 7.55 8.63 10.65 8.88 5.61 IQR 8.12 6.67 5.03 6.68 3.70 3.19 Mean 9.13 9.98 8.06 3.95 4.69 2.60 Median 2.18 1.72 1.70 2.49

to the left from 2004 to 2009. In total, there are to 1,506 observations for 5 multiples and ROE.

RESULTS AND DISCUSSION

In this study, the valuation errors of multiples were measured with median absolute error (MeAE). Wilcoxon rank sum is used to test the statistical difference between paired samples shown in Tables 2 and 3. If the

negative (positive) Wilcoxon value is less than -1.96 (greater than +1.96) and the p-value < 0.05, the paired distribution of valuation errors is statistically different at the 5% significance level since the null hypothesis is rejected. Then, the negative (positive) Wilcoxon value indicates that the valuation errors based on the method in row (column) is systematically larger (less) than the one in column (row). For instance, Table 2 demonstrates that the Wilcoxon

Table 2
Multiples valuation accuracy when benchmark multiple is estimated from plantation firms

	P/E	P/B	P/CF	P/S	P/TA
Performance Measure					
Mean Absolute Error (MAE)	0.66	0.60	0.72	2.76	0.60
Median Absolute Error (MeAE)	0.31	0.38	0.36	0.62	0.44
1st Quartile	0.11	0.22	0.15	0.30	0.21
3rd Quartile	0.59	0.62	0.58	1.20	0.71
Inter-Quartile Range	0.48	0.39	0.43	0.90	0.50
Wilcoxon value (p-value)					
P/B	-2.60				
	(0.01***)				
P/CF	-1.28	1.23			
	(0.20)	(0.22)			
P/S	-7.47	-5.86	-6.46		
	(0.00***)	(0.00***)	(0.00***)		
P/TA	-3.47	-1.19	-2.16	4.73	
	(0.00***)	(0.23)	(0.03**)	(0.00***)	

Notes: P/E = Price-to-Earnings, P/B = Price-to-Book Value, P/CF = Price-to-Cash Flow, P/S = Price-to-Sales. */**/*** represent significant at 10%/5%/1% levels, respectively

and p-value for the paired distribution of valuation errors of P/S (in row) and P/E (in column) multiples is -7.47 (0.00). Since the negative Wilcoxon value is less than -1.96 and the p-value is less than 0.05, the valuation errors of paired multiples are statistically different at the 5% significance level. The negative Wilcoxon value denotes the valuation errors based on P/S multiple (in row) is systematically larger than P/E multiples (in column). Stated differently, the negative Wilcoxon value means the P/E multiples (in column) is statistically superior to P/S multiple (in row) in terms of valuation accuracy.

Table 2 shows that when the plantation sector is used as the basis to select comparable firms. The results show that the price-

to-earnings (P/E) multiple tends to yield the most accurate valuation performance. This occurrence is based on two criteria. First, the valuation error (MeAE) for P/E is the lowest in all multiples. Second, the Wilcoxon rank sum test result shows the valuation performance of price-to-earnings multiple is statistically different with all paired multiples with the exception to price-to-cash flow multiple. The negative Wilcoxon value indicates the valuation errors for P/E multiple (in column) is systematically smaller than all multiples in the row. In contrast, the price-to-sales multiple is the worst valuation method in terms of valuation errors (MeAE); and it is also statistically inferior to all multiples according to Wilcoxon rank sum test.

Table 3
Multiples valuation accuracy when benchmark multiple is derived from plantation firms and profitability (ROE)

	P/E	P/B	P/CF	P/S	P/TA
Performance Measure					
Mean Absolute Error (MAE)	0.64	0.62	0.81	1.51	0.63
Median Absolute Error (MeAE)	0.30	0.30	0.33	0.57	0.34
1st Quartile	0.10	0.10	0.12	0.30	0.12
3rd Quartile	0.55	0.57	0.58	0.90	0.63
Inter-Quartile Range (IQR)	0.46	0.46	0.46	0.61	0.50
Wilcoxon value (p-value)					
P/B	-0.21				
	(0.83)				
P/CF	-0.60	-0.39			
	(0.55)	(0.70)			
P/S	-6.70	-6.88	-6.47		
	(0.00***)	(0.00***)	(0.00***)		
P/TA	-1.66	-1.43	-1.04	5.31	
	(0.10*)	(0.15)	(0.30)	(0.00***)	

Notes: P/E = Price-to-Earnings, P/B = Price-to-Book Value, P/CF = Price-to-Cash Flow, P/S = Price-to-Sales. **/*** represent significant at 10%/ 5%/ 1% levels, respectively.

When the ROE and industry membership are used to select the benchmark multiple, the price-to-earnings (P/E) and price-to-book value (P/B) multiples yield best valuation performance in terms of valuation errors (MeAE) followed by price-to-cash flow (P/CF), price-to-assets (P/TA) and price-to-sales (P/S) multiples (refer Table 3).

The Wilcoxon rank sum test demonstrates that the P/E valuation method is statistically indistinguishable to all paired multiples except for P/S multiple. Interestingly, the valuation performance of the P/S multiple is the worst in terms of valuation errors (MeAE), and it systematically produces bigger valuation errors than all paired multiples according to Wilcoxon rank sum test. Finally, the valuation errors (MeAE)

of all multiples are found to be improved after ROE is used as the control factor to select benchmark multiple. For example, the valuation error for P/B multiple was mitigated from 0.38 to 0.30. Interestingly, the results show that there is only one marginal improvement on the valuation performance of P/E multiple.

Overall, the current study indicates that P/TA and P/S are the most unreliable multiples in terms of valuation errors in both definitions of benchmark multiple as shown in Tables 2 and 3. Theoretically speaking, the P/S and P/TA multiples share a common trait, i.e., the economic means of a numerator is not matched by the denominator. This can be seen by the fact that the numerator of multiples, i.e.,

equity price, represents the economic value of the stock that held by equity investors. By contrast, the denominator of multiples, i.e., sales and assets, are economic variables for both equity investors and creditors. To illustrate this, the firm's total assets consist of total debts that are owned by creditors. Another example is that the firm has to use profit from sales to cover repayment of principal and interest on total debts that claimed by creditors. Thus, P/S and P/TA multiples clearly violate the consistency in the economic means and this phenomenon may cause mis-pricing (Damodaran, 2006).

Our empirical results are largely consistent with prior studies that investigated multiples in corporate valuation. First, our result shows that P/E multiple yields the smallest median absolute error in the plantation sector. Similarly, Schreiner and Spremann (2007) found that P/E multiple produces the smallest valuation errors compared to other multiples such as P/B, P/CF, P/S and P/TA for European firms. Consistent with Cheng's and McNamara's (2000) finding, this study revealed that the P/E multiple yields higher valuation accuracy compared to P/B. Furthermore, the current results also indicate that P/S multiple is the least accurate compared to P/E, P/B, P/CF and P/TA multiples. The concordance of the results was also uncovered in a study on the Bucharest Stock Exchange in Romania (Mînjina 2009). This denotes that P/S multiple is the least reliable multiple although it is difficult to be manipulated from the accounting perspective.

Finally, Tables 2 and 3 demonstrate that

the median absolute error (MeAE) and mean absolute error (MAE) differ significantly in terms of magnitude. We also can observe that most of the MAEs are located closely to first or third quarter of the valuation error distributions. Thus, we can infer that using MAE to identify relative performance of multiples is very sensitive to outliers and could lead to biased estimations. This result confirms our previous suggestion that using the average mean as a statistical estimator for valuation errors is not appropriate in valuation multiples.

CONCLUSION

The purpose of this article is to formulate methodologies of valuation multiples in agribusiness firms. Our article offers four important findings for analysts in pricing agribusiness (or traditional) firms with multiples: first, the median is a reliable and robust statistical estimator to estimate benchmark multiple and valuation performance; second, using ROE as a control factor on industry membership to estimate benchmark multiple leads to better valuation performance; third, the P/S multiple should be avoided in valuation context; and, the P/E multiple assures top valuation performance when pricing agribusiness (or traditional) firms.

Furthermore, market-based valuation multiples in this study indicate that earnings is the prime value driver in traditional industry because P/E multiple produces best valuation performance. Since stock price is a leading indicator for economic activities (Auret & Golding, 2012), we

suggest that the stock market perceives the asset utilization to be the core competencies of traditional firms in all economic cycles. Thus, analysts should view the efficiency of asset utilization as important criteria in pricing traditional firms.

Our study contributes to research on the use of valuation multiples. We have demonstrated how multiples can be used in the valuation of equities in agribusiness (or traditional) industry. Thus, our findings will help practitioners to use multiples more effectively. Our work can also serves as the benchmark in the formulation of future research on the effectiveness of this method of valuation.

REFERENCES

- Alford, A. W. (1992). The effect of the set of comparable firms on the accuracy of the price-earnings valuation method. *Journal of Accounting Research*, 30, 94-108.
- Auret, C., & Golding, J. (2012). Stock prices as a leading indicator of economic activity in South Africa: Evidence from the JSE. *Investment Analysts Journal*, 76, 39-50.
- Baker, M., & Ruback, R. (1999). *Estimating industry multiples*. Working Paper, Harvard University.
- Bhojraj, S., & Lee, C. M. C. (2002). Who is my peer? A valuation-based approach to the selection of comparable firms. *Journal of Accounting Research*, 40, 407-439.
- Cheng, C. S. A., & McNamara, R. (2000). The valuation accuracy of the price-earnings and price-book benchmark valuation methods. *Review of Quantitative Finance and Accounting*, 15, 349-370.

- Damodaran, A. (2005). Valuation approaches and metrics: a survey of the theory and evidence. *Foundation and Trends in Finance*, 1, 693-784.
- Damodaran, A. (2006). Damodaran on valuation: Security analysis for investment and corporate finance. New Jersey: John Wiley & Sons.
- Dittmann, I., & Weiner, C. (2005). Selecting comparables for the valuation of European firms. Retrieved April 2013 from http://ssrn.com/abstract=644101 or http://dx.doi.org/10.2139/ssrn.644101.
- Fidanza, B. (2008). The valuation by multiples of Italian Firms. *Corporate Ownership and Control*, 7, 228-237.
- Hammel, J. E., & Hodes, D. A. (1967). Factors influencing price-earnings multiples, *Financial Analysts Journal*, *23*, 90-93.
- Herrmann, V., & Richter, F. (2003). Pricing with performance-controlled multiples. *Schmalenbach Business Review*, *55*, 194-219.
- Imam, S., Chan, J., & Shah, S. Z. A. (2013). Equity valuation models and target price accuracy in Europe: Evidence from equity reports. *International Review of Financial Analysis*, 28, 9-19.
- Ivashkovskaya, I., & Kuznetsov, I. (2007). An empirical study of country risk adjustments to market multiples valuation in emerging markets: the case for Russia. *E-Journal Corporate Finance*, *3*, 26-52.
- Kim, M., & Ritter, J. R. (1999). Valuing IPOs. *Journal of Financial Economics*, *53*, 409-437.
- Lie, H., & Lie, E. (2002). Multiples Used to Estimate Corporate Value. *Financial Analysts Journal*, 58, 44-54
- Liu, J., Nissim, D., & Thomas, J. (2002). Equity valuation using multiples. Journal of Accounting Research, 40, 135-172.

- Kaplan, S. N., & Ruback, R. S. (1995). The valuation of cash flow forecasts: An empirical analysis. *The Journal of Finance*, 50, 1059-1093.
- Mînjina, D. I. (2009). Relative performance of valuation using multiples. Empirical evidence on Bucharest stock exchange. *The Review of Finance & Banking*, 1, 35-53.
- Michaud, R. O. (1990). Demystifying multiple valuation models. *Financial Analysts Journal*, 46, 6-8.
- Moore, D. S., & McCabe, G. P. (2005), *Introduction to the practice of statistics* (5th ed.). New York: W. H. Freeman Company.
- Murphy, J. E., & Stevenson, H., W. (1967). Price/ earnings ratios and future growth of earnings and dividends. *Financial Analysts Journal*, 23, 111-114.
- Norman, A. R., & Streiner, D. L. (2007). *Biostatistics: The bare essentials* (3rd ed.). New York: People's Medical Publishing House.
- Park, Y. S., & Lee, J. J. (2003). An empirical study on the relevance of applying relative valuation models to investment strategies in the Japanese stock market. *Japan and the World Economy*, 15, 331-339.
- Roosenboom, P. (2012). Valuing and pricing IPOs. *Journal of Banking & Finance*, *36*, 1653-1664.
- Russo, R. (2003). Statistics for the behavioural sciences: An introduction. East Sussex: Psychology Press.
- Schreiner, A., & Spremann, K. (2007). *Multiples and their valuation accuracy in European equity markets*. Retrieved April, 2013 from http://ssrn.com/abstract=957352 or http://dx.doi.org/10.2139/ssrn.957352